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A NEW SIMULATION-OPTIMIZATION MODEL FOR WILDLAND FIRE RESOURCE PRE-POSITIONING

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THESIS

A NEW SIMULATION-OPTIMIZATION MODEL FOR WILDLAND FIRE RESOURCE PRE-POSITIONING

by

Rachel A. Seeberger

December 2020

Thesis Advisor: Javier Salmeron-Medrano
Second Reader: Gerald G. Brown

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13. ABSTRACT (maximum 200 words)

Every day, using detailed weather forecasts, paired with reports on the moisture content of soil and vegetation, the Los Angeles County Fire Department (LACoFD) must decide where to pre-position firefighting equipment and personnel for the following day. For years, LACoFD has relied on their own expert judgment to make these costly decisions. In 2019, NPS student Zachary Scholz developed the Augmentation Optimization Model (AOM), a mathematically based decision tool to guide resource pre-positioning. Unfortunately, AOM relies on weak estimations of expected burned acreage, complicating result interpretation. We address this problem by developing a simulation to estimate "initial attack" area containment as a function of pre-positioned resources. These estimates inform the new AOM's objective, producing improved, realistic, and interpretable results. In addition, we have followed LACoFD feedback to incorporate accessibility and steepness of terrain, hand-crew resources, and solution evaluation. We also standardize assembled resources as mixes of engines and exchangeable personnel and reformulate the model so it generates and solves faster. Through an upgraded user interface, LACoFD is using the new AOM daily and analyzing alternatives of protection and cost. The results improve those of legacy AOM and LACoFD's manual solutions on the critical days tested. Moreover, we demonstrate that protection can benefit from augmentation policies not solely based on burning index.

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A NEW SIMULATION-OPTIMIZATION MODEL FOR WILDLAND FIRE RESOURCE PRE-POSITIONING

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ABSTRACT

Every day, using detailed weather forecasts, paired with reports on the moisture content of soil and vegetation, the Los Angeles County Fire Department (LACoFD) must decide where to pre-position firefighting equipment and personnel for the following day. For years, LACoFD has relied on their own expert judgment to make these costly decisions. In 2019, NPS student Zachary Scholz developed the Augmentation Optimization Model (AOM), a mathematically based decision tool to guide resource pre-positioning. Unfortunately, AOM relies on weak estimations of expected burned acreage, complicating result interpretation. We address this problem by developing a simulation to estimate “initial attack” area containment as a function of pre-positioned resources. These estimates inform the new AOM’s objective, producing improved, realistic, and interpretable results. In addition, we have followed LACoFD feedback to incorporate accessibility and steepness of terrain, hand-crew resources, and solution evaluation. We also standardize assembled resources as mixes of engines and exchangeable personnel and reformulate the model so it generates and solves faster. Through an upgraded user interface, LACoFD is using the new AOM daily and analyzing alternatives of protection and cost. The results improve those of legacy AOM and LACoFD’s manual solutions on the critical days tested. Moreover, we demonstrate that protection can benefit from augmentation policies not solely based on burning index.

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LIST OF ACRONYMS AND ABBREVIATIONS

AIC	Akaike Information Criterion
ACS	Acreage Containment Simulation
AOM	Augmentation Optimization Model
AOMS	Augmentation Optimization Model with Simulation
BI	Burning Index
BIR	Burning Index Ratio
BIT	Burning Index Threshold
CA	Captain
CART	Classification and Regression Tree
ERC	Energy Release Component
FF	Firefighter
FFS	Fire Fighter Specialist
gpm	Gallons per Minute
LAC	Los Angeles County
LACoFD	Los Angeles County Fire Department
LFM	Live Fuel Moisture
NFDRS	National Fire Danger Rating System
R^2	Coefficient of Determination
RAWS	Remote Automated Weather Station
RMSE	Root Mean Square Error
ROC	Receiver Operator Characteristic
ROI	Return on Investment
SC	Spread Component
VIF	Variance Inflation Factor
WIMS	Weather Information Management System
WIRAS	Wildfire Initial Response Assessment System

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EXECUTIVE SUMMARY

The 2020 wildfire season brought unprecedented damage to the United States. Over 13.5 million acres burned across the country, with 4 million in the state of California alone (National Interagency Fire Center 2020, National Oceanic and Atmospheric Administration [NOAA] 2020). These fires are estimated to cost over $130 billion in total economic losses (Puleo 2020).

Preparedness, a federal wildfire funding program, aims to pre-position firefighting resources in areas more likely to experience a fire (U.S. Department of the Interior 2020). Relocating assets to these sites increases the likelihood that they will be available to quickly suppress a wildfire. “Initial attack,” the rapid first response to a wildland fire, can help prevent the fire from becoming large and causing serious damage to life, property, and the environment. This makes effective resource pre-positioning a key priority for fire departments. However, balancing the capability needed to prevent large fires and the cost of resources is not easy.

Los Angeles County Fire Department (LACoFD) has a long history of fighting large fires. In September 2020, the Bobcat Fire burned over 100,000 acres in Los Angeles County, destroying nearly 90 homes and costing an estimated $80 million in fire suppression efforts (Stanfield 2020). Every day, LACoFD uses resource pre-positioning, or augmented staffing, to enhance its wildland fire suppression efforts across 21 sub-areas (geographical regions managed by LACoFD, established by climactic zone and proximity to remote weather stations). For years, LACoFD personnel have relied solely on their own expert judgement to make these costly decisions. Forecasted weather and fire danger indices have been the driving factors behind augmentation. Specifically, a fire danger index called the burning index (BI) measures the difficulty of fire containment (Schlobohm and Brain 2002). LACoFD typically augments when a sub-area’s BI exceeds its BI threshold (BIT), a high quantile of historical BI.

Scholz (2019) developed the Augmentation Optimization Model (AOM), a mathematically based decision tool, as a proof of concept to guide LACoFD daily augmentation plans. AOM uses logistic regression to predict the probability of fire start for each of the 21 sub-areas. AOM also uses multiple linear regression to predict expected burned acreage given that a fire occurs. These regressions are provided to an optimization model that includes available equipment and personnel, the cost of activating off-duty personnel and moving equipment, and a maximum budget. The model calculates the optimal feasible resource pre-positioning to minimize expected population displacement.

The AOM prototype needs improvement, especially due to inaccurate estimates for burned acreage, which make AOM's solutions difficult to interpret. This research improves AOM by developing a discrete-event simulation model of initial attack and refining the optimization. We also perform an in-depth analysis of the 2015–2018 burned acreage data and conclude that it cannot be predicted accurately.

The Acreage Containment Simulation (ACS) estimates acreage containment as a function of pre-positioned resources in each sub-area. In ACS, personnel and engines arrive over a designated time horizon and lay hose on the right and left flank of a fire. ACS is constructed using data on engine water capacity, hose length, hose lay rates, and sub-area terrain and accessibility. Acreage containment is calculated using the perimeter of hose laid around a 45-degree sector of a circle, representing the right and left flanks closing toward each other. To model initial attack, we terminate the simulation after 30 minutes. We simulate over 3 million combinations of resources, each for 1,000 replications. We perform regressions on ACS outputs for each sub-area to build an approximating, closed-form expression of initial-attack containment as a function of pre-positioned resources.

ACS outputs supply a new optimization model, the Augmentation Optimization Model with Simulation (AOMS). AOMS calculates the optimal placement of seven types of firefighting resources (extending AOM with hand crews) across all sub-areas. AOMS incorporates a new objective function, whose main term is an expected loss that balances population density and acreage containment across all sub-areas. AOMS' key decision variables account for engine transfers between sub-areas, personnel transfers between sub-areas, off-duty personnel called up to a sub-area, and the final resource configuration selected for each sub-area. We allow the transfer of engines and personnel individually, which generates more flexible solutions than legacy AOM. We also provide users with the ability to evaluate solutions by fixing or encouraging their adoption and include a more intuitive input and output design. Overall, AOMS produces a solution in approximately half the time of legacy AOM.

We delivered AOMS to LACoFD in October of 2020, and LACoFD began using it daily and providing feedback for analysis. We assess AOMS' solutions for multiple days in October and November 2020, including a day when a fire did occur. Initial analysis shows that AOMS may outperform LACoFD's solutions in two ways: (a) by reducing cost, and (b) by recommending augmentation to sub-areas that are not necessarily above BIT, but where a serious fire could occur (as on November 5, 2020).

We also compare AOMS to AOM by replicating the resource packages that AOM produced for December 6, 2017. AOMS' cost is lower, due to improved transfers. Most importantly, for that day, AOMS' own solution recommends augmenting resources to the Beverly Hills sub-area, where a 422-acre fire occurred. Neither LACoFD (which adopted a very costly solution) nor AOM augmented to Beverly Hills. For that date, AOMS outperforms AOM in two metrics related to 30-minute initial attack: expected acreage containment and expected persons protected (based on population density). We conclude that AOMS can calculate more effective solutions than AOM and LACoFD.

This research has notably enhanced problem representation, solution interpretation, and overall tool utilization. Thus, we feel confident recommending LACoFD continues using AOMS to help guide their daily pre-positioning plans. We also recommend LACoFD's feedback be used for continued maintenance and improvement of all AOMS components.

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I. INTRODUCTION

A. BACKGROUND

Wildfires pose an increasing threat to many regions of the United States. In 2018, more than 58,000 fires burned close to nine million acres across the country (Hoover and Hanson 2020). These fires cost $25.6 billion in damages and resulted in the loss of over 3,000 lives (U.S. Fire Administration 2018). In 2020, unprecedented fires burned over 13.5 million acres across the United States, damaging more than 18,000 structures and causing economic damage equivalent to that of a Category 4 or 5 hurricane (National Interagency Fire Center 2020, Puleo 2020). AccuWeather Founder and Chief Executive Officer Dr. Joel N. Myers states that the “estimated damage total and cumulative economic loss of all 2020 wildfires is expected to be between $130 billion and $150 billion” (Puleo 2020). California was particularly vulnerable during the 2020 fire season, with over four million acres burned – more than doubling the statewide burn record set in 2018 (National Oceanic and Atmospheric Administration [NOAA] 2020). Between August and the end of September 2020, five of the six largest recorded wildfires in California scorched the state.

Each year, the federal government spends billions of dollars to combat wildfires. In 2020, over $3.5 billion worth of fire suppression efforts were spent nationwide (National Interagency Fire Center 2020). The United States Department of the Interior divides wildland fire management funding into a variety of programs, namely: preparedness, suppression, fuels management, facilities, burned area rehabilitation, and science (U.S. Department of the Interior 2020). The Preparedness Program focuses on training and response planning, as well as ensuring that staff and equipment are pre-positioned in locations most likely to experience a fire. Pre-positioning resources daily, a process referred to as “augmentation,” is essential for the rapid response to and suppression of a wildfire. This rapid response is referred to as “initial attack.” The United States Department of Agriculture Forest Service defines initial attack as “the actions taken by the first resources to arrive to a wildfire to protect lives and property, and prevent further extension of the fire” (United States Department of Agriculture [USDA] Forest Service 2020). Extinguishing new fire starts via initial attack is critical for keeping fires under control, minimizing damage, and preventing evacuations. Resource augmentation helps position resources closer to likely fire starts and thus increases the likelihood of a successful initial attack. In the remainder of this thesis, the terms resource pre-positioning and augmentation are used interchangeably.

1. Los Angeles County Fire Department Augmentation Problem

Wildland fires are especially hazardous to the densely populated Los Angeles area in California. In 2018, wildfires burned over 63,000 acres within Los Angeles County (LAC), and in 2019, nearly 10,000 acres were burned. This equates to fire losses of $314 million and $119 million for each year, respectively (LAC Fire Department [LACoFD] 2019). In 2020, the Bobcat Fire burned over 115,000 acres within LAC, making it one of the largest fires in LAC history (Columbia Broadcasting System Los Angeles [CBSLA] Staff 2020). To combat this threat, LACoFD devotes substantial resources to suppressing wildfires, and augments daily across its diverse areas of responsibility.

The mission of LACoFD is "to protect lives, the environment, and property by providing prompt, skillful and cost-effective fire protection and life safety services" (LACoFD 2020). LACoFD has three objectives that relate to this research:

1. **Protection of life**: minimize both population and firefighter loss;
2. **Incident stabilization**: contain 95% of all wildland fires to 10 acres (4 Ha) or less; and,
3. **Property and environment protection and conservation**: minimize the total wildland acreage burned.

LACoFD is responsible for protecting the lives and property of four million residents living in the cities and unincorporated areas of LAC. LACoFD has almost 5,000 employees and answers almost 400,000 annual emergency calls, with an annual budget of $1.2 billion (LACoFD 2020). Across the county's 4,700 square mile land area, LACoFD operates and maintains 174 fire stations, each outfitted with an assortment of firefighting equipment and staff. These stations allow LACoFD to respond to a variety of incidents and provide widespread coverage of high-risk wildland fire areas.

LACoFD employs specialized equipment staffed by multiple different types of personnel. LACoFD's fleet of trucks consists mainly of Type I engines, Type III engines, Type VI engines, and water tenders. Firefighting personnel are divided into three categories: firefighter (FF), firefighter specialist (FFS), and captain (CA). Figure 1 displays each engine type (see the caption for personnel staffing configurations). LACoFD can also employ hand crews (consisting of inmates assigned to manually cut fire lines) in its fire response. Other resources (e.g., fire suppression aids, bulldozers, helicopters, and air tankers) can be utilized, but are not incorporated into this study.

From left-to-right and top-to-bottom, are Type I, III, and VI engine variants, and a water tender. Each Type I structural engine is staffed with a CA, a FFS, and one or two FFs. Each Type III off-road vehicle carries a CA, a FFS and two FFs. Each Type VI off-road patrol engine carries a FF and an optional CA. Each water tender carries a FFS. In respective order, images are sourced from: Johanson (2010a), Deyo (2011), Johanson, (2010b), and Johanson (2010c).

Figure 1. LACoFD Rolling Equipment

Effective resource pre-positioning is a key priority for LACoFD. However, balancing the capability needed to prevent large fires and the cost of resources is not easy. In 2018, LACoFD reached out to the Naval Postgraduate School seeking a mathematically based method to help guide daily resource augmentation.

B. CURRENT METHODS

It is LACoFD's responsibility to recognize wildfire threat and to augment resources as necessary. This first requires a daily assessment of weather conditions, as well as the examination of detailed reports on the moisture content of soil and vegetation. Subsequently, LACoFD must decide if and where to pre-position firefighting resources in order to minimize the extension and population displacement of a potential wildfire.

The weather data used to advise resource pre-positioning are collected from an array of 21 Remote Automated Weather Stations (RAWS) across the five climatic zones of LAC. These zones are referred to as Los Angeles Basin, Santa Monica Mountains, Santa Clarita Valley, High Country, and Antelope Valley. Figure 2 displays the five climactic zones and most RAWS. This study uses RAWS as sub-areas for the purpose of pre-positioning, where each RAWS may contain multiple fire stations.

Daily weather measurements from each RAWS are electronically reported to the Weather Information Management System (WIMS) and used to forecast fire danger with a series of indices formulated by the National Fire Danger Rating System (NFDRS) (Deeming et al. 1978, Bradshaw et al.1983).

Two of these indices, the spread component (SC) and energy release component (ERC), offer a measure of the difficulty of fire containment, while a third index, called the Keetch-Byram Drought Index, indicates soil moisture levels (Keetch and Byram 1968, Rothermel 1972, Schlobohm and Brain 2002). These three indices assist LACoFD in determining wildfire potential and are described thoroughly in Scholz (2019).

Black dots locate most of the 21 RAWS. Santa Clarita, Santa Catalina Island, and San Clemente Island are not pictured.

Figure 2. LAC Climatic Zones and RAWS. Adapted from LACoFD (2018).

The NFDRS also provides the burning index (BI), which is developed using both the SC and ERC, along with Byram's method for calculating flame length (Byram 1959). The BI ultimately measures the "relative difficulty of containing a fire through the interrelationship of flame length and fire line intensity" (Schlobohm and Brain 2002). LACoFD has established a BI threshold (BIT) for each of the five climactic zones within LAC. A sub-area's BIT is defined as the 97th percentile of all recorded BIs in its climactic zone, and is intended to attract pre-positioning efforts. LACoFD often augments for a RAWS when BI exceeds the BIT, or when the average BI across all RAWS within a climatic zone exceeds the BIT for that zone. Conversely, LACoFD rarely considers augmenting to RAWS under BIT.

For years, LACoFD has relied solely on expert judgment to pre-position resources. Forecasted weather and BI have been the driving factors behind the number of individual resources augmented. In particular, staffing is more likely to occur during periods of high winds and low relative humidity, a condition referred to as “red-flag weather” (Scholz 2019).

Scholz (2019) developed the Augmentation Optimization Model (AOM) to help LACoFD decide where and when to augment their resources most effectively. AOM predicts fire start, burned acreage, and subsequently provides an optimal allocation of resources to minimize population displacement across the abovementioned RAWS sub-areas. AOM’s output is intended as a recommendation for pre-positioning, and decisions are ultimately made by experienced LACoFD personnel.

Using WIMS data spanning from 2000 to 2018, AOM utilizes a separate logistic regression for estimating the probability of fire start in each LAC climactic zone. Each of these regressions contains multiple predictor variables, ranging from BI, temperature, and wind to other factor variables such as day of the week and the specific RAWS within the climactic zone. These models use stepwise regression to minimize the Akaike Information Criterion (AIC) and have been validated with a receiver operator characteristic (ROC) curve (Akaike 1973, Fawcett 2006).

For the prediction of burned acreage, AOM uses a return-on-investment (ROI) function through multiple linear regression. Given a combination of pre-positioned staff and equipment, forecasted weather, and fire-danger indices, the regression estimates the expected burned acreage in the event that a wildland fire should occur. Using a “capability score” derived from Cox and Hemme (2018), AOM is able to account for all firefighting resources available in a single predictor. Resource pre-positioning records are only available from 2015 to 2018, so AOM’s regression model was developed with limited data.

Both the probability of fire and expected burned acreage regressions are inputted into an integer linear program that determines the optimal placement of firefighting resources across the 21 RAWS. This model aims to minimize the proportional expected population displacement across LAC, and calculates the optimal transfer and employment of both on-duty and off-duty personnel and engines (Scholz 2019). Ultimately, each RAWS is assigned an optimal resource package, that is, a combination of the six firefighting resources considered: Type I engine (with three staff), Type III engine, Type VI engine (with one FF), water tender, an additional FF on a Type I engine, and an additional CA on a Type VI engine. Each engine is staffed by its respective combination of FFs, FFSs, and CAs.

C. RESEARCH CONTRIBUTIONS AND SCOPE

LACoFD used AOM during the 2019 fire season, and their experience suggested attractive improvements. The most important enhancement relates to current estimations of burned acreage, which are highly prone to error. Instead, we have worked closely with LACoFD to replicate the initial containment process, and we design a simulation that produces more interpretable and accurate results. Additionally, some factors have not yet been studied as potential contributors to fire start and extension. LACoFD is also interested in the daily tradeoff between augmentation capability and its cost, rather than being limited to a fixed budget.

This research develops improved methods to plan daily pre-positioning of firefighting resources for LACoFD. Specifically, the following contributions are outlined:

- **Regressions:** We analyze new factors that may affect prediction of fires and their extension.

- **Representation:** We improve AOM's representation of the problem by: (a) introducing a simulation to estimate initial area containment as a function of pre-positioned resources, and (b) using the simulation results to develop a new optimization model.

- **Flexibility:** We increase AOM's flexibility by allowing the reassignment of personnel and engines separately.

- **Fixed solutions:** We allow LACoFD to fix complete solutions or suggest parts of them, which is essential for their analysts to compare plan effectiveness.

- **Run time:** We improve solution time (AOM's speed including building and preprocessing all input data, and optimization run time).

- **Diverse solutions:** We provide a range of solutions each day, which enables LACoFD analysts to assess tradeoffs between cost and protection.

- **Improved user interface:** We improve AOM input and output design for easier use and result interpretation by LACoFD analysts. We provide spreadsheet view and control of all parameters, some of which had been hidden in AOM internal source code.

This research is also limited in several ways: We are allocating resources across RAWS sub-areas within LAC, rather than fire stations. This is because we do not have station-specific fire, weather, and other data with which to carry out our analysis. In addition, this keeps AOM within a reasonable size. Finally, while weather data date back to 2000, augmented staffing data are only available from 2015 to 2018.

Ultimately, this research develops and computationally implements an efficient and capable decision support tool to help guide LACoFD's augmented staffing plans. As with AOM, these plans are recommendations, and decisions will ultimately be made by experienced professionals.

D. THESIS OUTLINE

The remainder of this thesis is organized as follows. Chapter II surveys previously published work related to the optimization of resource allocation for wildland fires. Chapter III discusses the data and methods used in this study. These methods extend the work of Scholz (2019) by first re-examining the predictions of probability of fire and burned acreage. Subsequently, we develop a simulation in order to estimate acreage containment; this will serve as an additional input to our reformulated optimization model. Chapter IV presents the results for several LACoFD scenarios. Finally, Chapter V offers concluding thoughts and suggestions for future research.

II. LITERATURE REVIEW

Multiple studies on the allocation of resources in wildfire mitigation have been conducted prior to this research. Wiitala (1999) develops a non-linear integer program to determine the optimal set of initial attack resources to suppress a wildfire. Wiitala takes into account the cost of resource transportation and use, hose line construction rates, as well as the size and rate of spread of a fire to help dispatchers identify the "most efficient initial attack response" (Wiitala 1999). The study aims to minimize cost – derived from both monetary costs and expected resource losses.

Wiitala's model aids in decision making after a wildfire has started. A second study takes a similar approach, modeling fire propagation and emergency vehicle dispatch in order to minimize forest loss and fire suppression costs (Yang et al. 2017). The authors develop a two-layer logistics system. The first layer consists of a fire propagation model. This layer is intended to reflect the evolution of a fire once it starts, accounting for the flame-igniting attributes of wildfires, as well as the factors contributing to their spread. Using a propagation forecast, fire sites are prioritized by their emergency level. The second layer consists of a multi-objective vehicle routing problem optimization model. In both rapid- and slow-propagation scenarios, this model works to minimize travel time and costs, with emphasis on higher-priority fire sites. Neither Yang et al.'s nor Wiitala's models take into account resource pre-positioning.

Another approach to wildfire resource allocation involves the use of a stochastic process. Wiitala and Wilson (2008) develop a discrete-event stochastic simulation model called the Wildfire Initial Response Assessment System (WIRAS), which mimics the dynamics of fire start, progression, and suppression. The simulation models the deployment of firefighting resources in response to a yearly, random stream of wildfires, which vary in behavior, location, and time of arrival. Ultimately, WIRAS calculates a variety of statistics (see Figure 3), including acres burned, numbers of fires escaping initial attack, and cost of resource utilization. Fire planners can use WIRAS results to help improve their resource deployment and dispatch policies.

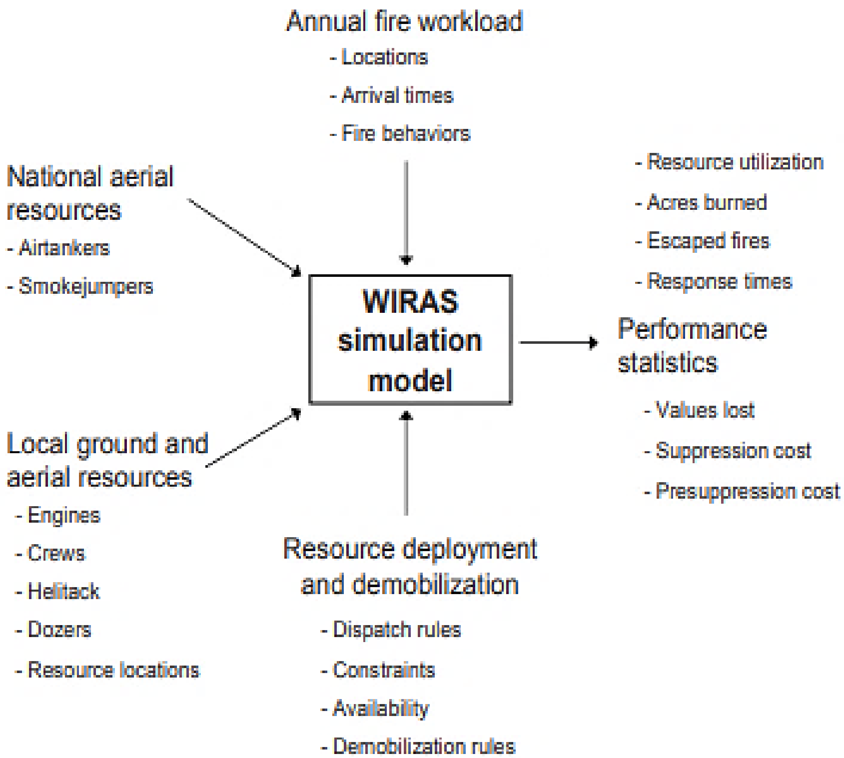

Figure 3. WIRAS Overview. Source: Wiitala and Wilson (2008).

Rahn (2010) determines the hose-lay and production rates for different numbers of personnel at varying slopes and within varying brush types. Hose-lay rate is defined as the "rate at which a 100-foot section of hose can be laid by firefighting personnel," while production rate refers to the "rate at which fire break line can be created by clearing a line of brush." Both of these tactics, laying hose and clearing brush, are crucial to fire suppression. Our research extends the work of Cox and Hemme (2018) and Scholz (2019) in the way the effects of these two tactics are measured and employed.

Cox and Hemme (2018) develop an integer linear program to determine resource augmentation. This model is based on a "capability score," paired with daily forecasted BI data. The capability score combines Rahn's research with fire station data as shown in the Equations (1) and (2), where: P is the total number of personnel in the pre-positioned resources, excluding any personnel assigned to water tenders; H is the total number of hoses available; $\overline{\delta}$ is average hose lay rate (linearly interpolated by the function $L(x)$); ρ

is the weighted average production rate of the Type VI engine and additional CA (both derived from Rahn's 2010 research); ω is engine water capacity; and N is the number of each resource available. The capability score is conditional on the ratio of personnel to hoses for each resource package in order to reflect Rahn's (2010) report stating that the greatest increase in personnel efficiency occurs when the ratio of personnel to hoses increases from two to three.

$$\begin{aligned} Capability &= \overline{\delta} H\left(1+\frac{\omega_{WT}N_{WT}}{\omega_{T1}N_{T1}+\omega_{T3}N_{T3}+\omega_{T6}N_{T6}}\right) \text{ if } \frac{P}{H} \geq 3, \\ &\text{where } \overline{\delta} = L\left(\frac{P}{H}\right) \end{aligned} \tag{1}$$

$$\begin{aligned} Capability &= \overline{\delta} H\left(1+\frac{\omega_{WT}N_{WT}}{\omega_{T1}N_{T1}+\omega_{T3}N_{T3}+\omega_{T6}N_{T6}}\right)+\rho_{T6}N_{T6}+\rho_{CA}N_{CA} \text{ if } \frac{P}{H} < 3, \\ &\text{where } \overline{\delta} = L\left(\frac{P-N_{T6}-N_{CA}}{H-N_{T6}}\right) \end{aligned} \tag{2}$$

Scholz (2019) adapts Cox and Hemme's capability score to estimate the expected burned acreage of a fire. Scholz implements this capability score as a predictor in a multiple linear regression model to estimate the expected burned acreage of a wildland fire at each RAWS. Scholz then develops AOM, which uses probability of fire and expected burned acreage, to minimize expected population displacement across all RAWS.

Scholz acknowledges the difficulties in estimating burned acreage, which in turn frustrates AOM's ability to produce meaningful results to LACoFD planners. Our research aims to correct this, with solutions based on estimated containment during the initial attack phase, instead of total burned acreage.

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III. METHODOLOGY

We first have verified that the fire probability prediction models developed by Scholz (2019) do not improve by adding accessibility and terrain as new predictors (provided by LACoFD for this study). Thus, the area under the ROC curve for each LAC climactic zone's logistic regression remains between 0.682 and 0.803. The data used to formulate these models are identical to those used by Scholz (2019).

The following sections discuss the difficulties in improving AOM's weak regression to estimate burned acreage. As an alternative, we develop a simulation of fire containment during initial attack, which is more accurate and interpretable. We then develop a new optimization model that incorporates those simulated containment values.

A. ESTIMATED BURNED ACREAGE OF WILDLAND FIRE

To predict the burned acreage of a wildland fire, AOM utilizes an ROI function through multiple linear regression. Given any combination of resource configuration, forecasted weather, and fire-danger indices, the regression model estimates expected burned acreage in the event that a wildland fire should occur. To quantify the combined capability of firefighting resources, Scholz's model uses the abovementioned Cox and Hemme (2018) capability score as a predictor. Scholz's model was produced without terrain and accessibility as predictors, and generated a 10-fold cross-validated coefficient of determination (R^2) value of 0.1096. R^2 indicates the percentage of variance explained by a model (Faraway 2016). While higher R^2 values are better than lower ones, the precise R^2 value that constitutes a good model varies according to the application. For this research, a cross-validated R^2 value of approximately 11% is not sufficient to constitute an acceptable model.

We now analyze the difficulties in predicting burned acreage and explore if accessibility and terrain can help improve that prediction. Rstudio was used to generate all plots and models (Rstudio Team 2020). We ultimately conclude that we cannot estimate burned acreage acceptably given the data available, as described in the following sections.

1. Initial Data Exploration

Data pertaining to burned acreage span the years 2003 to 2004, 2006 to 2007, 2012 to 2013, and 2015 to 2018. However, data on augmentation is only available for the years 2015 to 2018. This is due to limitations regarding LACoFD's access to augmented staffing plans prior to 2015 (Scholz 2019). The data provided contain the number of acres burned in a fire, the corresponding weather, BI, and fuel moisture forecast from the previous day, and the number of resources stationed at that RAWS when the fire occurred. Resource structure is adopted from Scholz (2019).

A total of 2,244 observations were recorded from 2015 to 2018. Table 1 depicts the number of observations by climactic zone, as well as by RAWS.

Table 1. Burned Acreage Observations by Climactic Zone and RAWS

Climactic Zone	RAWS	Number of RAWS Observations	Number of Climactic Zone Observations
Los Angeles Basin	Santa Fe Dam	208	1,069
	Henninger Flats	37	
	Claremont	137	
	Whittier	539	
	San Rafael	58	
	Tonner Canyon	90	
Santa Monica Mountains	Cheseboro	35	528
	Malibu	29	
	Beverly Hills	160	
	Leo Carrillo	15	
	Malibu Canyon	38	
	Topanga	14	
Santa Clarita Valley	Saugus	89	291
	Acton	34	
	Del Valle	51	
	Newhall Pass	74	
High Country	Camp 9	60	248
	Whitaker I-5	48	
Antelope Valley	Poppy Park	113	108
	Saddleback	43	
	Lake Palmdale	372	

Whitter Hills RAWS recorded the highest number of observations, while Leo Carrillo and Topanga RAWS had 15 or fewer observations each. This wide disparity amongst numbers of observations presents a challenge for predictive models. Due to the drastic differences in terrain and vegetation between RAWS, it is essential to, at a minimum, utilize RAWS as a categorical predictor. Because of the lack of observations, however, this is not possible. Similarly, there are few observations for the climactic zone Antelope Valley, so it is not possible to create separate models for each climactic zone. Hence, AOM utilizes a single model with factor variables for climactic zone. We use a similar approach later in this section.

An additional element of data exploration involves analysis of the number of large fires versus small fires within each RAWS. LACoFD is interested in containing fires to 10 acres or less, so we generate histograms to display the historical number of fires of certain sizes, in increments of five acres. A final category groups all fires over 100 acres. See Figures 4 through 8.

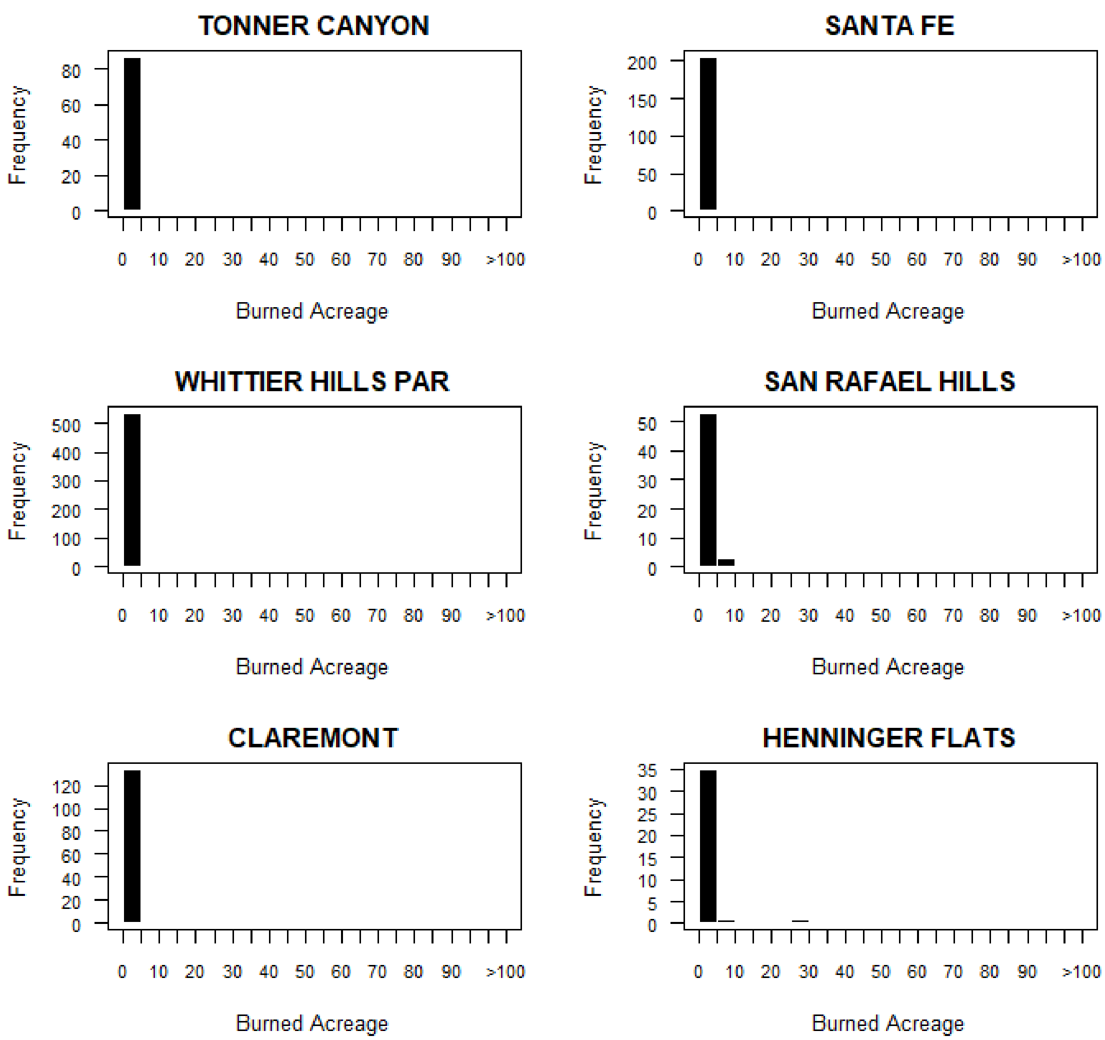


Figure 4. Histogram of Fire Sizes for LA Basin

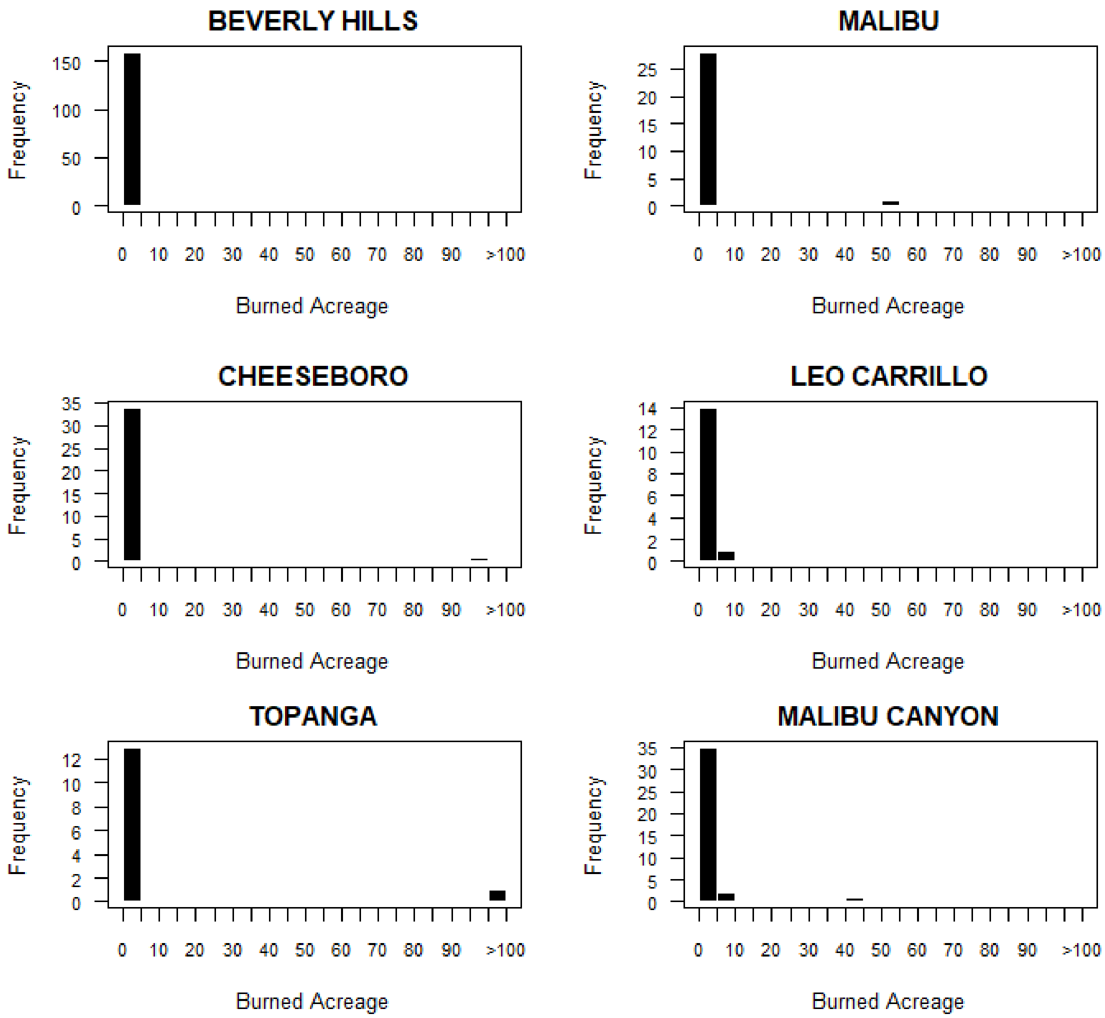


Figure 5. Histogram of Fire Sizes for Santa Monica Mountains

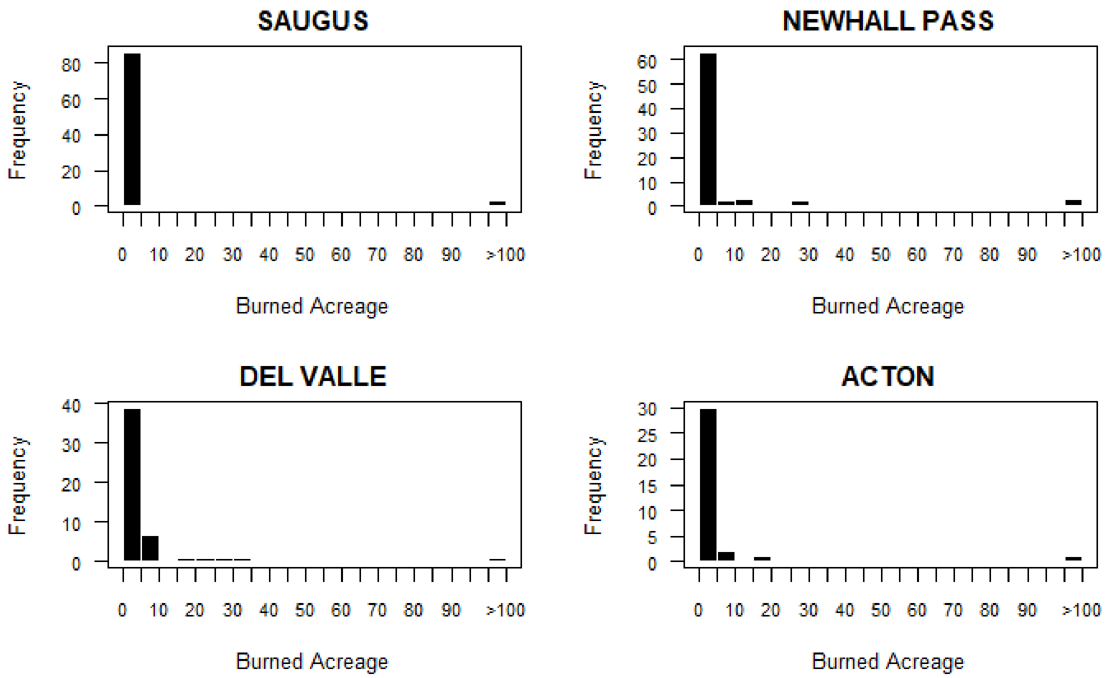


Figure 6. Histogram of Fire Sizes for Santa Clarita Valley

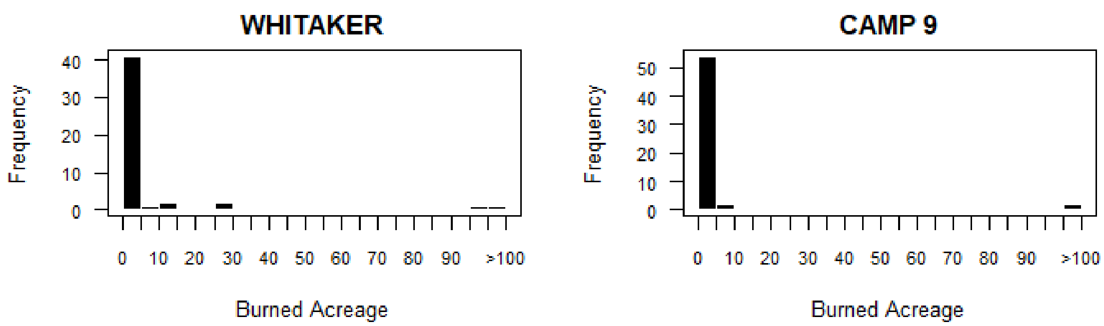


Figure 7. Histogram of Fire Sizes for High Country

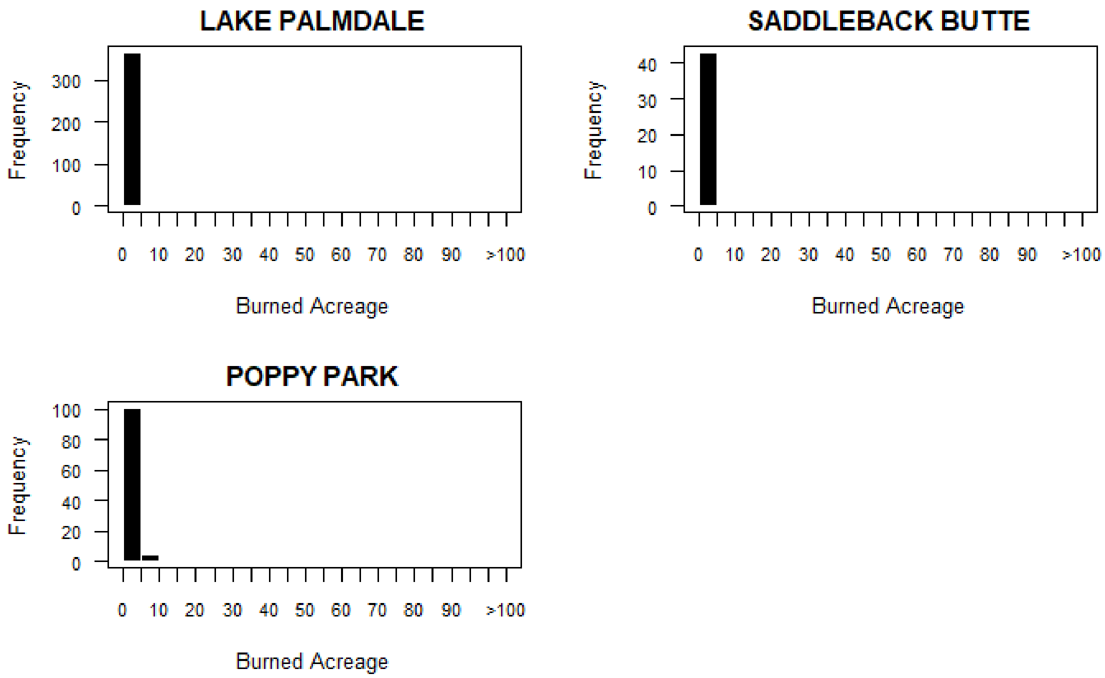


Figure 8. Histogram of Fire Sizes for Antelope Valley

These histograms reveal the complexity of predicting burned acreage. As mentioned in Chapter 1, one of LACoFD's objectives is to augment in order to keep fires from spreading beyond ten acres; however, the vast majority of historical fires burned five acres or less. This creates a challenge for predictive models, as they are unable to discern between which predictors actually contribute to large fires.

We are also interested in the impact of BI on the spread of a wildfire. We analyze the data to see if large fires are more likely to occur when the BI exceeds the BIT. Two histograms of burned acreage are displayed for each RAWS – one in which BI is below the BIT and one in which BI is at or above the BIT. The BI to BIT ratio is referred to as the burning index ratio (BIR). See Figures 9 through 13.

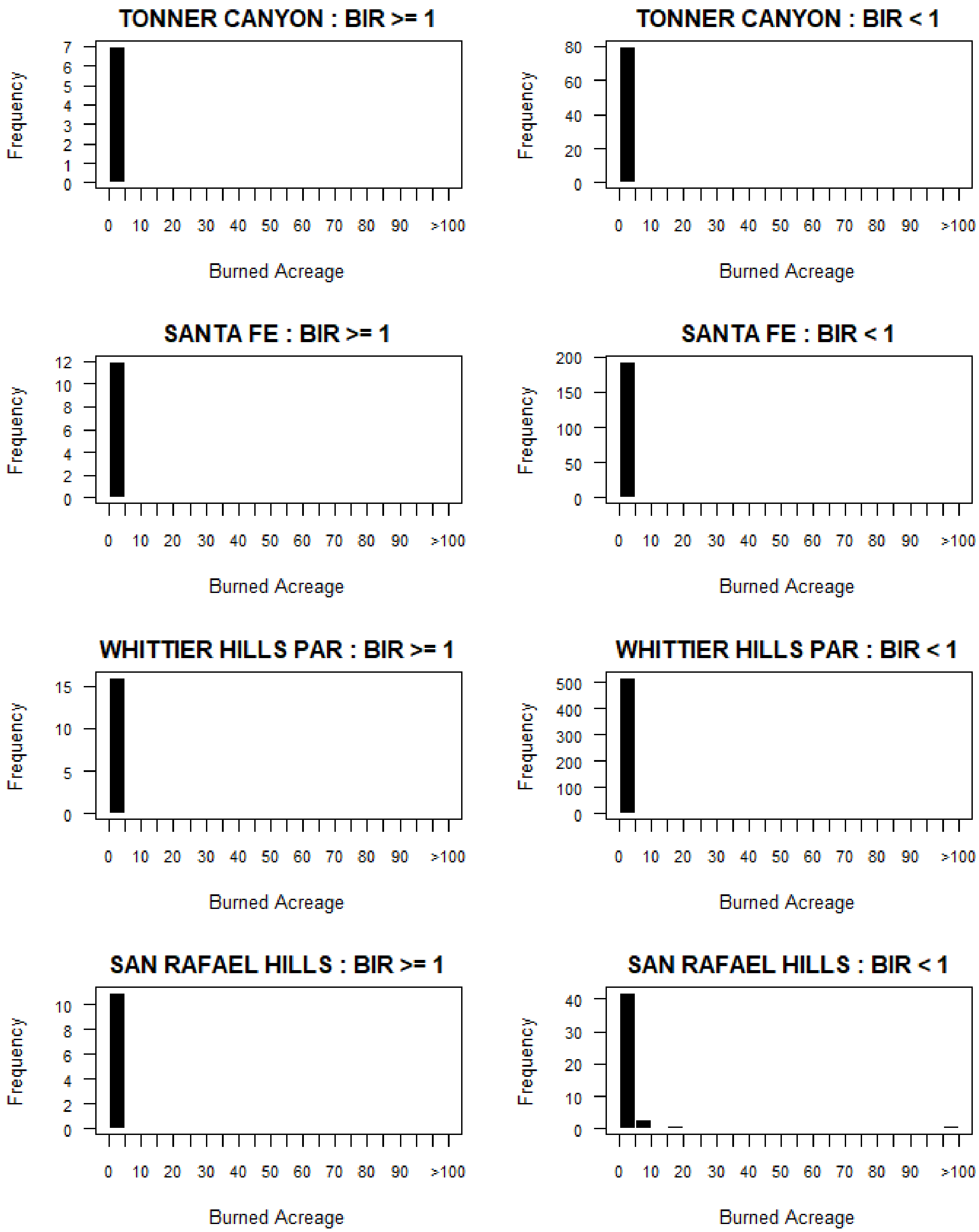


Figure 9. Histogram of Fire Size by BIR for LA Basin

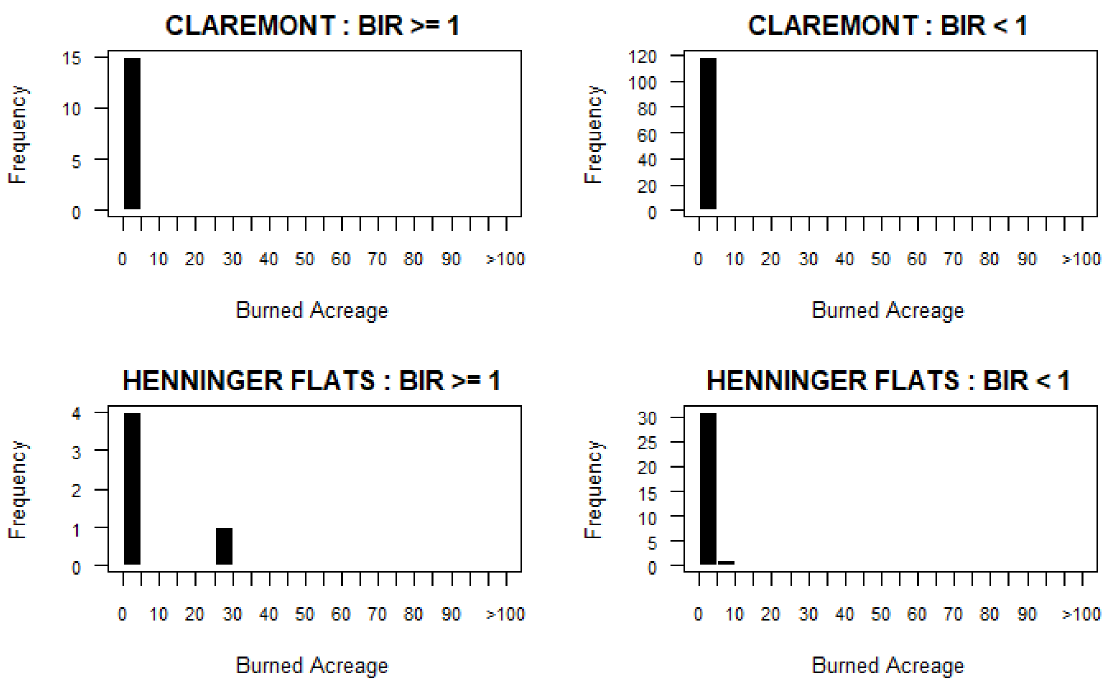


Figure 9 (continued). Histogram of Fire Size by BIR for LA Basin

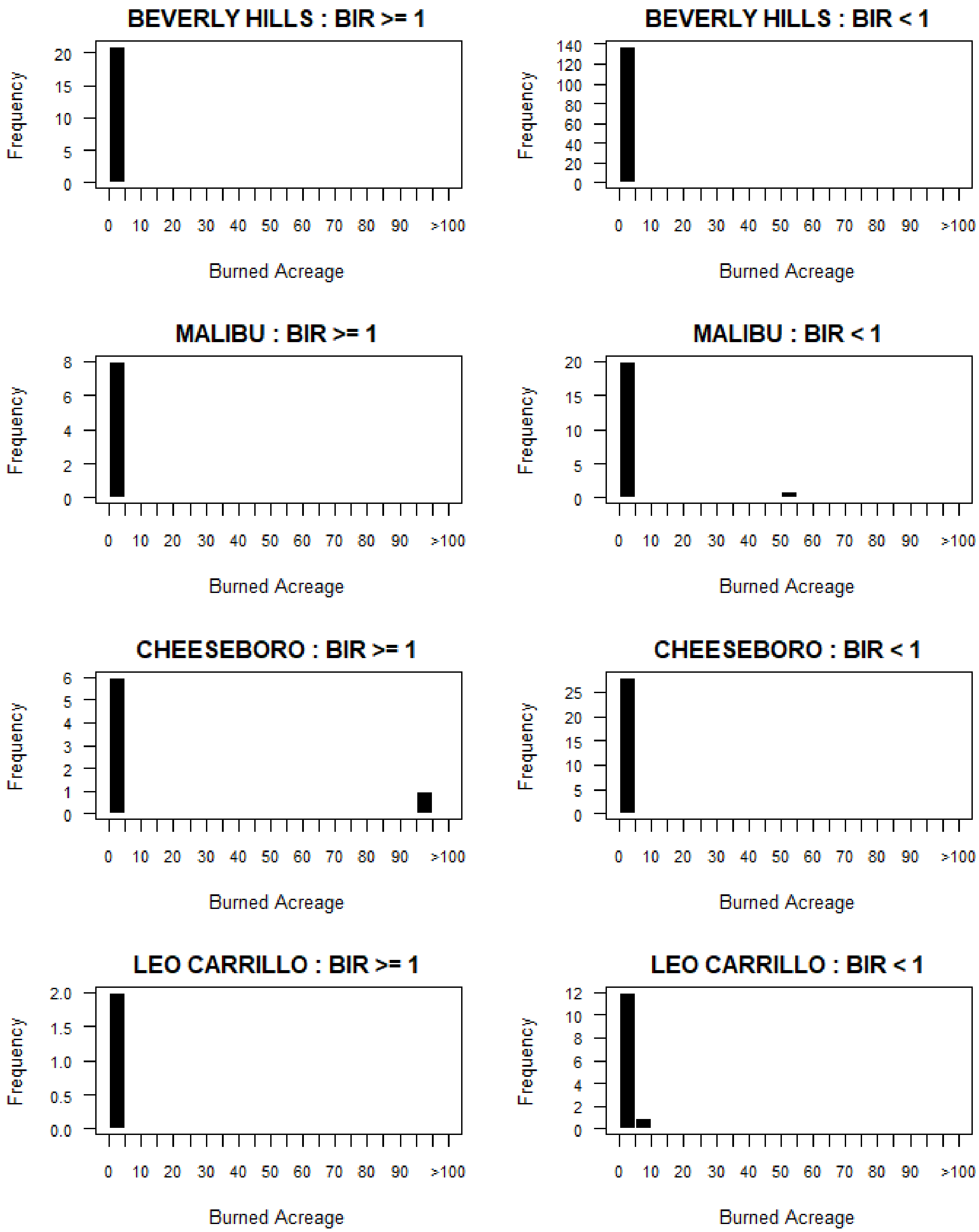


Figure 10. Histogram of Fire Size by BIR for Santa Monica Mountains

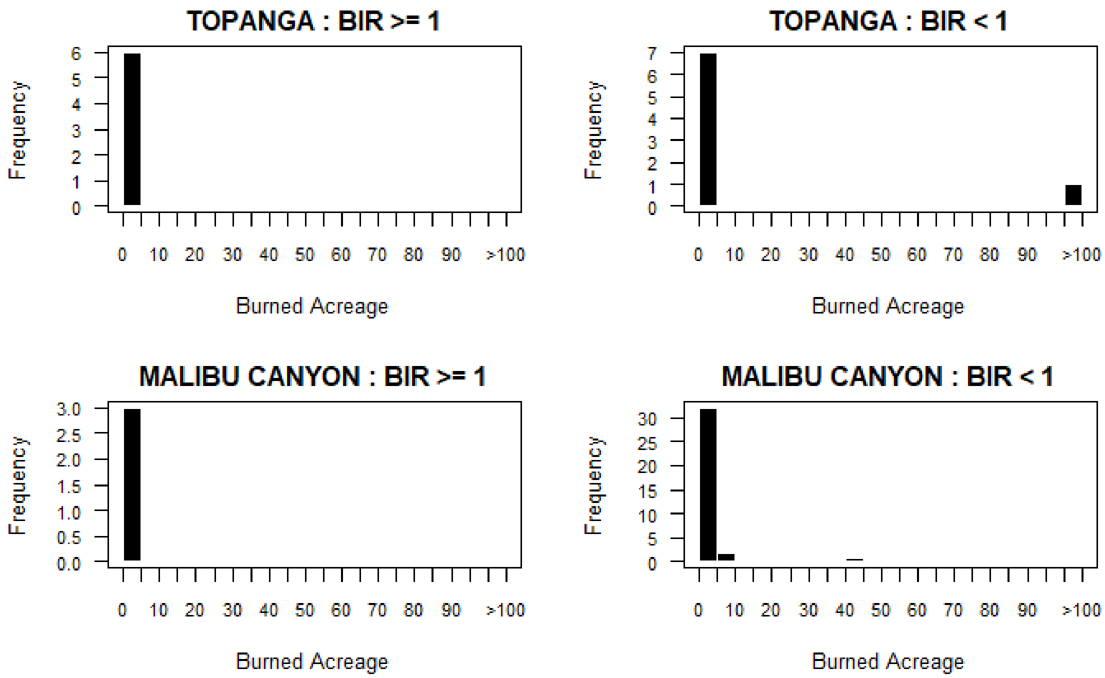


Figure 10 (continued). Histogram of Fire Size by BIR for Santa Monica Mountains

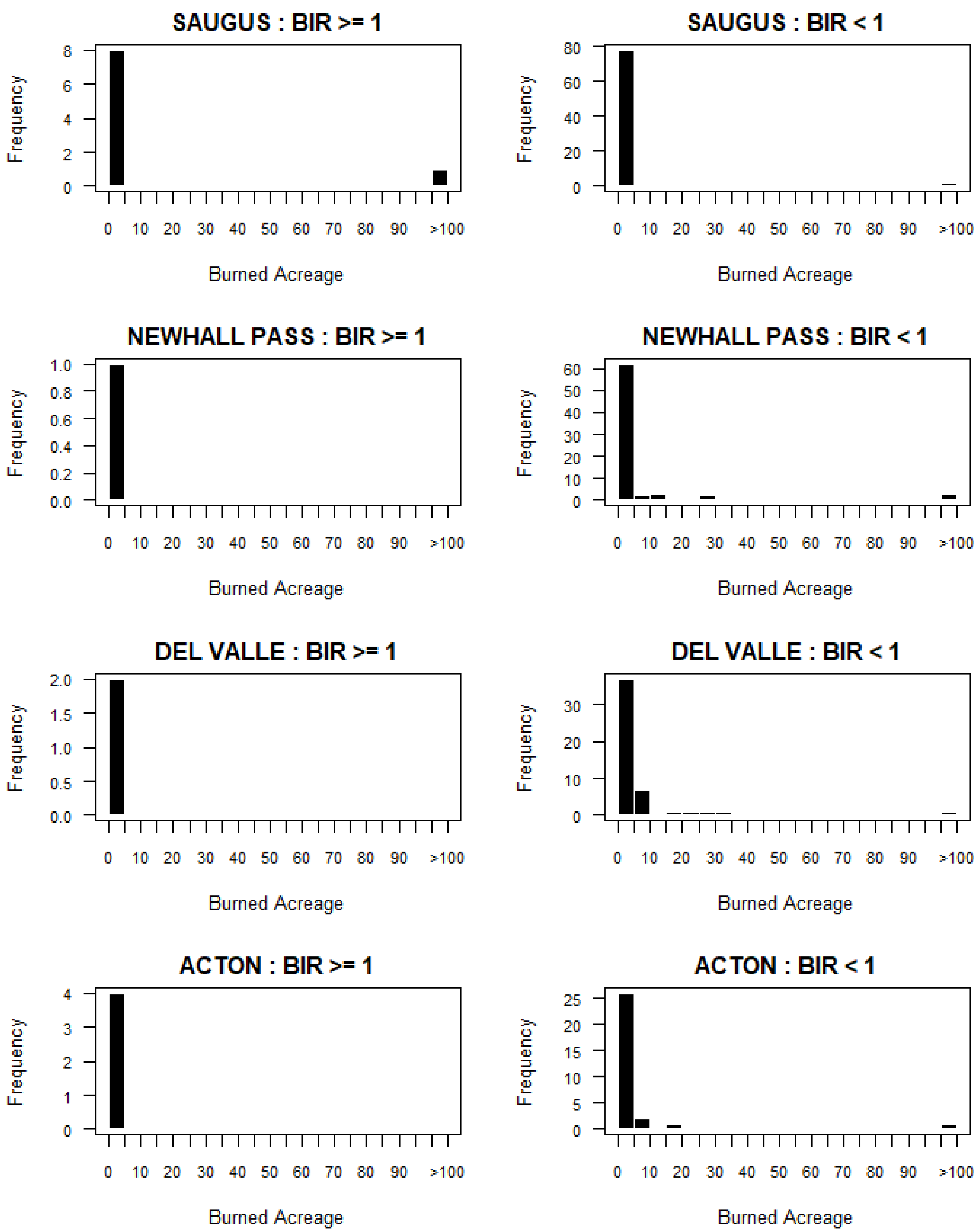


Figure 11. Histogram of Fire Size by BIR for Santa Clarita Valley

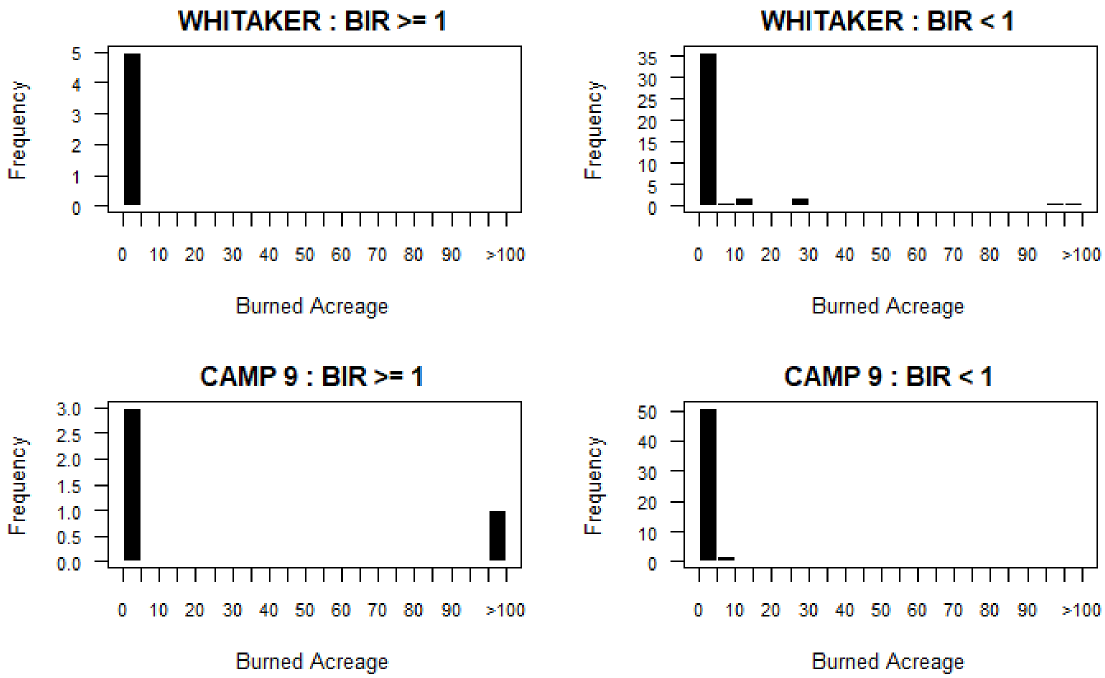


Figure 12. Histogram of Fire Size by BIR for High Country

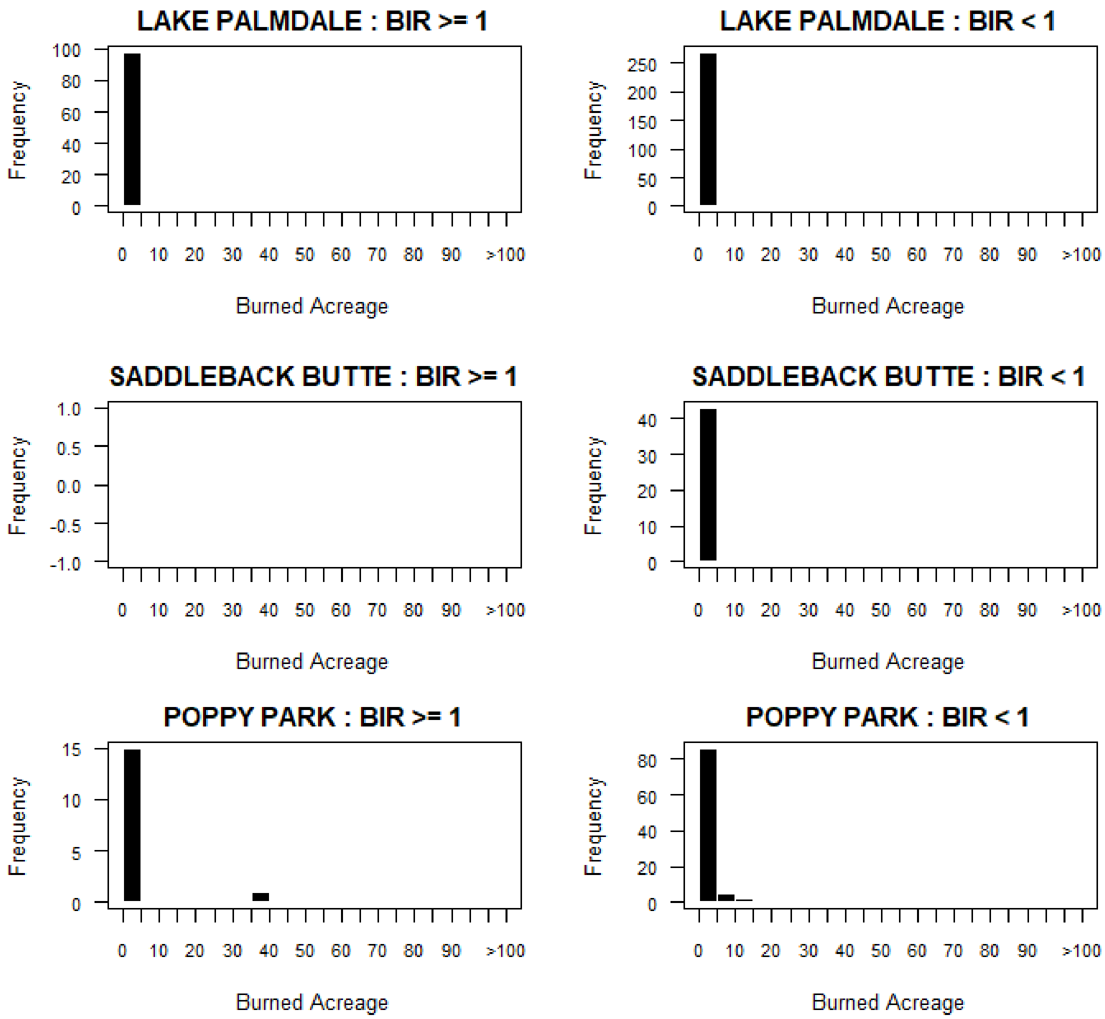


Figure 13. Histogram of Fire Size by BIR for Antelope Valley

These histograms reveal that BI is not a clear indicator of a fire size. Using Pearson's correlation test, we find a correlation of 0.12 between BI and burned acreage across all observations (Laerd Statistics 2020). Pearson's correlation coefficient indicates the strength of a linear relationship between two variables, and a coefficient of 0.12 indicates a weak linear relationship between BI and burned acreage. To account for differences in climactic zone BIT, BIR is also analyzed for correlation with burned acreage. Figure 14 displays BIR versus burned acreage for all observations. Due to the majority of observations falling below one acre, a plot using a more visually discernable natural logarithmic scale is displayed in Figure 15. The observations are divided into two groups in order to illustrate whether or not augmentation was conducted for the RAWS in which each fire occurred.

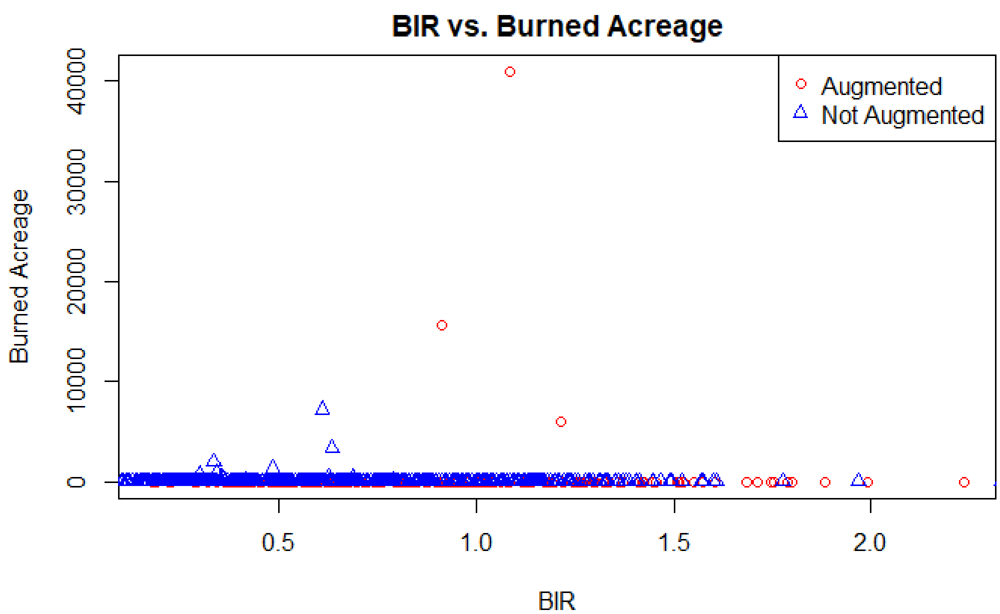


Figure 14. BIR vs. Burned Acreage

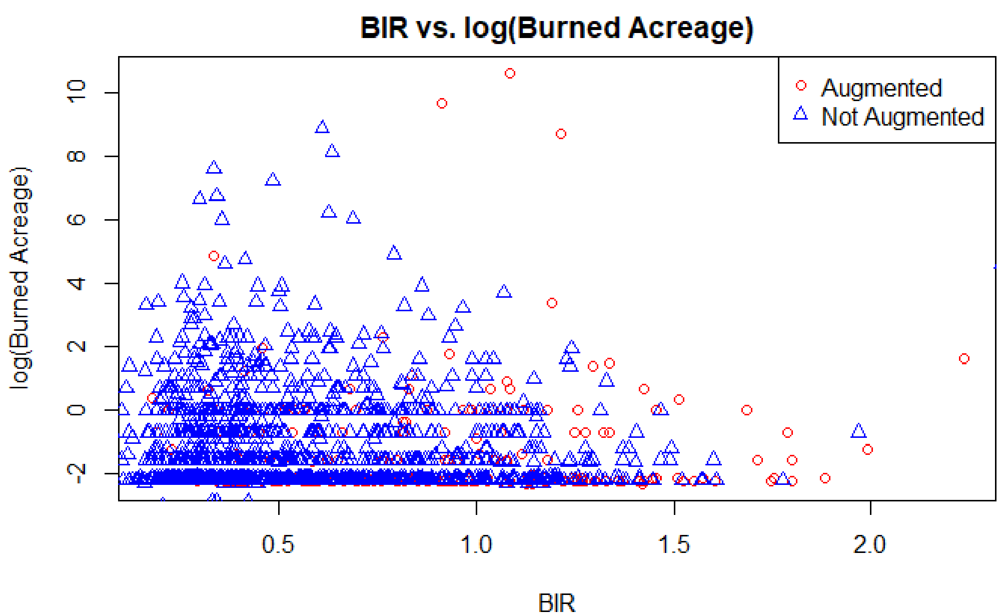


Figure 15. BIR vs. log(Burned Acreage)

Using Pearson's correlation test, we find a correlation of 0.05 between BIR and burned acreage across all observations. The plots reiterate that there is little relationship between the variables. Actually, Figure 15 indicates a negative relationship between BIR and burned acreage, which is counterintuitive. The two groups of observations also reveal that there is minimal relationship between augmentation and the burned acreage of a fire. In fact, the two largest fires occurred on days when augmentation had occurred for that fire's respective RAWS, which adds further complexity to the problem: it may falsely cue the regression that augmenting contributes to a larger fire (a remark already noted by Scholz).

In the following sections, we attempt to improve Scholz's burned acreage estimate using these data. Given these statistical forays, combined with the attempts below, we conclude that we cannot accurately predict burned acreage with the data available.

2. Multiple Linear Regression

For this study, LACoFD has provided new data on average terrain steepness and accessibility for each RAWS. We are interested in determining if these factors contribute to burned acreage. We produce several multiple linear regression models, each with these new predictors. Each model is validated with 10-fold cross-validation (Faraway 2016). To approximate a normal distribution, the burned acreage response variable is transformed using the natural logarithm for all regressions.

a. New Predictors

We develop a model using stepwise regression to minimize the AIC. We first generate a multiple linear regression model using all predictors and test it for multi-collinearity using variance inflation factors (VIFs). If one or more predictors have a VIF of approximately 10 or higher, predictors are removed (one at a time) from the model until all predictors have VIFs lower than 10. A "small" model is created using backwards stepwise regression on this model with all predictors. A "large" model is generated using all predictors, plus interaction terms. Stepwise regression, in both forward and backward direction, is used to find the optimal model between the small and large models.

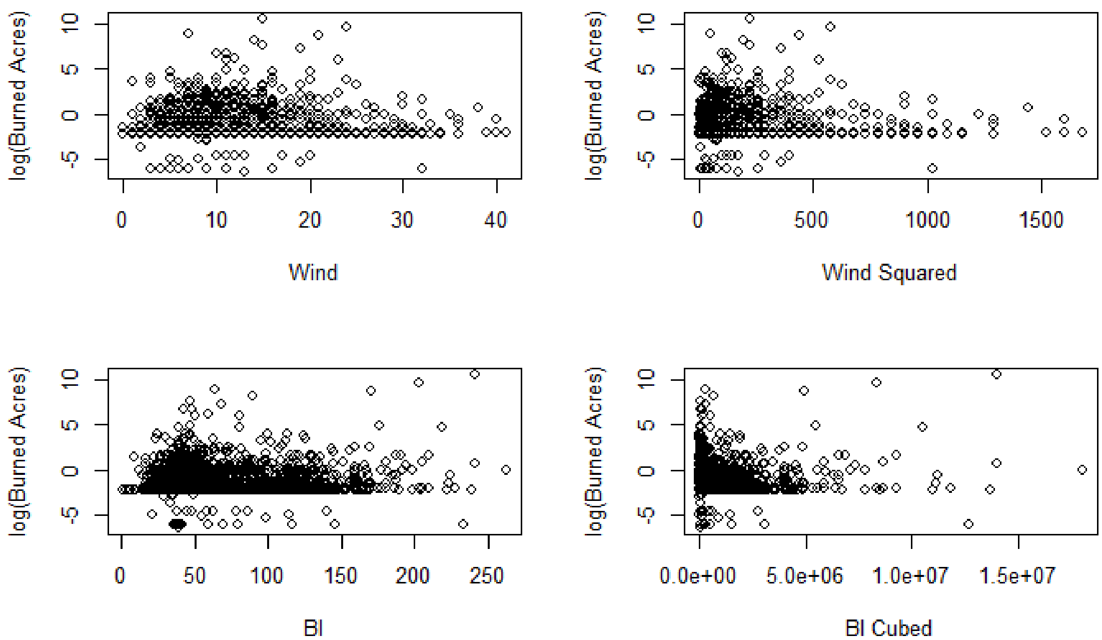
Using 10-fold cross-validation, the regression generates an R^2 value of 0.1078. It is important to note that due to the random nature of cross-validation, the random sequence generated influences results. Scholz (2019) used a different random generator in the original AOM validation process, so comparison is reasonable, but not exact. All results in this report will utilize an identical random seed, 4541, in RStudio.

For the Antelope Valley climactic zone, live fuel moisture (LFM) is not recorded. Due to the dry nature of vegetation in this desert area, it is not deemed significant. Because the multiple linear regression accounts for all climactic zones in one model, it is not possible to use LFM as a predictor in AOM. A second model is produced in which all Antelope Valley LFM values are set to 52, the minimum of all LFM values accounted for in the dataset. Using the same stepwise regression described previously, we produce a multiple linear regression. 10-fold cross-validation reveals an R^2 value of 0.0924, which is very low. Thus, the burned acreage regression in the original AOM by Scholz (2019) does not improve by adding the new predictors.

b. Predictor Transformations

In order to examine which predictors are candidates for potential transformations, we plot predictors against the response variable. Based on the general shape of plots, we attempt transformations on predictors. These transformations are again plotted and examined for signs of a more linear trend. We observe that with quadratic and cubic transformations for wind and BI, respectively, the trends become slightly more linear (see Figure 16). However, the decreasing trends are counterintuitive.

Stepwise regression using these transformations, as well as the new predictors terrain and accessibility, results in an R^2 value of 0.1067. In conclusion, transformations of predictors do not improve the regression by Scholz (2019).



The plot of Wind Squared vs. log(Burned Acreage) has a more linear shape than that of Wind vs. log(Burned Acreage). Likewise, the plot of BI Cubed vs. log(Burned Acreage) has a more linear shape than that of BI vs. log(Burned Acreage). Linear models can perform better when the relationship between predictors and the response is clearer. We transform the variables in these ways.

Figure 16. Predictor Transformations

c. *Multi-Day Fires*

The data available do not indicate the duration of a fire. Thus, it is unclear whether or not a fire was extinguished in a single day or lasted for multiple days or weeks. The acreage burned from a multi-day fire is not applicable to an augmentation problem, as the priority of augmentation is initial attack on the day a fire begins. In multi-day fires, additional resources are brought in for which AOM does not account. Multi-day fires are also typically much larger, and thus they skew the burned acreage data.

The burned acreage dataset only contains one observation for every fire that occurs, while the extensive weather dataset contains observations for every day and indicates whether or not a fire was occurring on that day. Therefore, we probe the weather dataset for multi-day fires and attempt to remove these observations from the burned acreage data. We assume that a multi-day fire has occurred if a fire appears on two or more consecutive days in the same RAWS. Upon examination of the weather dataset, however, we discover that there are numerous data gaps between days. Many days in the weather dataset have no record for any RAWS, and it is unknown if a multi-day fire occurred or not. Thus, we do not pursue this approach.

d. Removal of Outliers

Of the 2,244 fire observations, only 50 fires burned more than 10 acres. The remaining 2,194 observations record fires of 10 acres or less. The largest fire recorded burned 41,000 acres – a clear outlier when compared to the rest of the data.

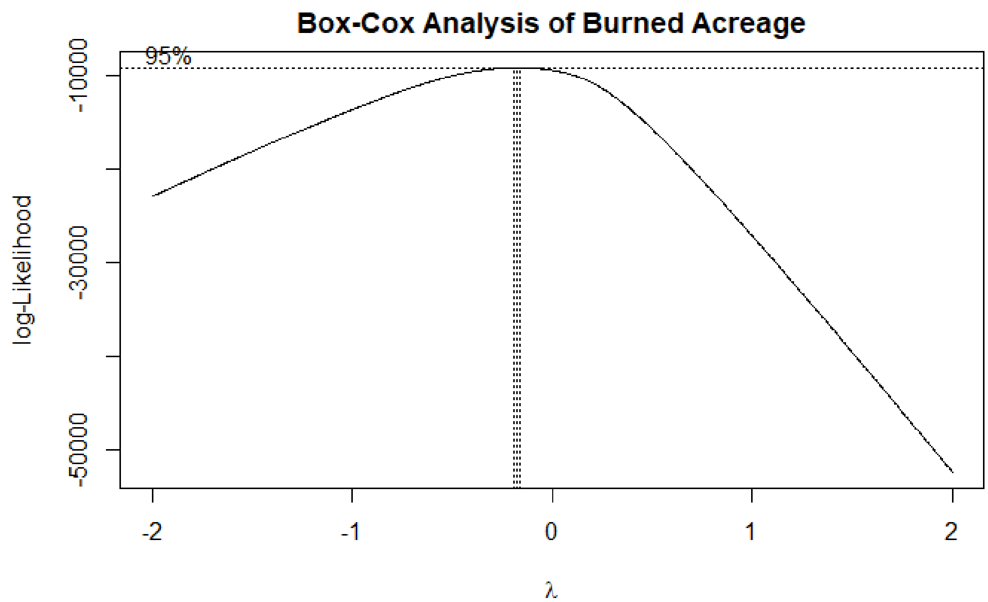
To evaluate if outliers are worsening model estimations, we remove observations if their burned acreage falls above a particular "cutoff point." We set these cutoff points at 50, 100, 1,000, 5,000, and 10,000 acres. For each cutoff point, we generate a model using stepwise regression to minimize AIC and evaluate it by 10-fold cross-validated R^2. The removal of outliers, in all instances, results in a lower cross-validated R^2 than 0.1096 - that of AOM. We conclude that removing outliers does not improve the burned acreage estimation by Scholz (2019).

3. Classification and Regression Tree

A final attempt at predicting the burned acreage of a wildland fire involves the use of a Classification and Regression Tree (CART). This approach is used to predict categorical variables (Faraway 2016). The burned acreage data available are continuous, but can be discretized into ranges so that they become factors.

Within the burned acreage data, there are 1,791 fires less than 1 acre, 403 fires between 1 and 10 acres, and 50 fires greater than 10 acres. These ranges are used to define the fire size categories "small," "medium," and "large." While LACoFD considers a "small" fire to be 10 acres or less, due to the abundance of observations below 10 acres, the categories are further divided into 0–1 ("small") and 1–10 ("medium") acres. Each observation is labeled with its corresponding category, and a CART is generated. The tree is pruned using the "sample error mean plus one standard deviation" rule. The resultant tree has no branches, which is referred to as a stump (James et al. 2017). This indicates that the tree is predicting all observations to fall into the same category – in this case, the "small" one. Using the predictors available, the tree cannot differentiate between the categories.

A second approach involves preserving the continuous burned acreage data, and utilizing a Box-Cox analysis of the burned acreage variable. The Box-Cox method suggests a transformation for the response variable using diagnostic plots (Faraway 2016). Figure 17 displays an output using the Box-Cox function from the "MASS" (Modern Applied Statistics with S) package in Rstudio (Venables and Ripley 2002).



The curve depicts log-likelihood of burned acreage for a range of transformations from -2 to 2. The parameter λ is selected to maximize log-likelihood of the response, and denotes the optimal transformation for the response (Venables and Ripley 2002).

Figure 17. Box-Cox Plot of Burned Acreage

The location of the optimal λ denotes the optimal transformation for the response. It is common to choose a λ that is near optimal for a model, but easier to understand. In this instance, we select a λ value of -0.25. The new response variable is defined as $a^{-0.25}$, where *a* represents burned acreage. A CART is again generated and pruned with the "sample error mean plus one standard deviation" rule. The resultant tree predicts acreages with accompanying frequencies, as displayed in Table 2.

Table 2. CART Predictions

Predicted Acres Burned	Number of Observations
0.976	98
0.841	7
0.919	271
0.904	1,324
0.831	10
0.876	61
0.812	8
0.766	10

As depicted, the CART never predicts a burned acreage greater than one acre. In closing, we see that both CART attempts also fail to predict burned acreage with the data available.

B. ESTIMATION OF CAPABILITY

We also consider the possibility of altering the predictor that reflects the capability of LACoFD resources. LACoFD provided a document containing a capability score, from 0 to 10, for specific packages within each RAWS. A value of 0 represents a package minimally capable of containing fire in the given RAWS, whereas 10 represents a package capable of containing any fire. Each package contained a numeric value for the Type I engine, Type III engine, Type VI engine, Water Tender, additional FF on a Type I engine, and additional CA on a Type VI engine. Three packages were scored for each RAWS: a "baseline" package containing the baseline values for each individual resource within that RAWS, a "maximum" package containing the maximum possible value for each resource within that RAWS, and a "minimum" package containing the minimum possible value for each resource within that RAWS. A total of 63 resource packages were scored for capability.

Unfortunately, there are too few data points given each of the 21 RAWS should have its own capability estimator. We do not rule out the possibility that this approach may lead to better results should LACoFD provide additional capability scores in the future.

C. ACREAGE CONTAINMENT SIMULATION

In this section, we develop the Acreage Containment Simulation (ACS). This estimates a measure of short-term fire containment capability, in acres. ACS is a discrete-event simulation where engines and personnel arrive sequentially, over a designated time period (e.g., 30 minutes or 1 hour), and gradually add to a hose-lay effort. This prevents overestimating containment, as would be the case if we assumed that all engines assigned to a RAWS contribute to fire containment immediately.

1. Parameters

ACS is constructed using data related to engine capacities, hose lay rates, and RAWS characteristics. Table 3 depicts the water capacity of each engine type.

Table 3. Engine Water Capacities

Engine	Water Capacity (gallons)
Type I	500
Type III	750
Type VI	250
WT	3,000

In addition to different water capacities, engines also carry different numbers of hose packs. Each hose pack contains a 100-foot section of hose. A firefighting team can only lay as much hose as is available. Each Type I and Type III engine carry eight hose packs. Each Type VI carries four hose packs.

Hose lay rates are derived from Rahn (2010) and Cox and Hemme (2018). For this study, hose lay rate is measured in feet per minute. Table 4 depicts the hose lay rates for varying personnel numbers at a 0% slope.

Table 4. Average Hose Lay Rates at 0% Slope. Adapted from Rahn (2010); Cox and Hemme (2018).

Personnel (Including FFs on Engine)	Average Hose Lay Rate [feet/min]
3	35.97
4	45.25
5	88.50
6	94.34

Finally, we use data on RAWS terrain and accessibility, as well as average water replenishment “sortie” time. Terrain is measured on a scale of 0 to 10 — 0 representing “table top flat” and 10 representing “cliff areas prevalent.” Accessibility is also measured on a scale from 0 to 10 — 0 representing no accessibility and 10 representing a dense urban road network. Average sortie time describes the average time for an engine to leave the scene of a fire, refill with water, and return to the scene of the fire. LACoFD provided Table 5 to reflect these values.

Table 5. RAWS Characteristics. Adapted from Freeman (2020b).

RAWS	Terrain	Accessibility	Avg. Sortie Time (minutes)
Santa Fe Dam	2	9	9
Henninger Flats	10	1	57
Claremont	2	8	12
Whittier	5	9	18
San Rafael	6	6	30
Tonner Canyon	7	2	45
Cheseboro	9	1	54
Malibu	8	3	45
Beverly Hills	5	8	21
Leo Carrillo	7	2	45
Malibu Canyon	10	2	54
Topanga	8	3	45
Saugus	5	9	18
Acton	6	5	33
Del Valle	8	3	45
Newhall Pass	8	4	42
Camp 9	10	1	57
Whitaker I-5	10	0	60
Poppy Park	4	4	30
Saddleback	2	4	24
Lake Palmdale	2	4	24

2. Assumptions

We make the following assumptions in order to simulate the response to a fire:

1. Time “zero” (the beginning of the simulation) is when the first engines arrive at the fire site. One Type I engine is always on scene at time zero. All Type VI engines and water tenders, if available, are also on scene.

2. Engine inter-arrival times follow a uniform distribution between two and five minutes.

3. After time zero, all available assembled resource types have equal probability of arriving next.

4. One person from every engine takes on a supervisor's role (does not contribute directly to hose-lay effort).

5. The maximum number of hose lays that can form during the simulation is two.

6. The maximum number of personnel on one hose is six.

7. Hose lays form on the right and left flank of the fire, separated by a 45-degree angle.

8. At a terrain level of 0, hose lay occurs at the rates provided in Table 4. At a terrain level of 10, hose lay occurs at 75% of the rates provided in Table 4. Hose lay rates for all other terrains are interpolated.

9. Let E be the number of engines on scene. If water capacity falls below $100 \cdot E$ gallons, a water tender, if available, will sortie. If a water tender is not available, a Type I engine will sortie.

10. Engines pump water at a rate of 10 gallons per minute (gpm).

11. Resources cannot be called in from another RAWS within the time horizon considered.

Next, we discuss and justify the above assumptions:

- Assumption (1) describes the first engines on scene when the simulation begins. Because Type VI engines are often used to scope out the scene of a fire before other engines arrive, we assume all Type VI engines are on scene at time zero. Because water tenders are relatively scarce resources (there may be only one water tender available out of a number of total resources), but arrive faster than Type I and Type III engines, they are assumed to be on scene at time zero. We also assume that a Type I engine is on scene, because every resource package contains at least one Type I engine, and because Type I engines are a main contributor to hose lay. This Type I engine can be staffed by three or four personnel.

- Assumption (2) allows for randomness in the time between engine arrivals. We select a relatively short time interval in order to balance a realistic interval between arrivals with the need to allow enough engines to arrive in 30 minutes (in order to discern their impact on containment).

- Assumption (3) is intended to make engine arrivals more realistic. All resource types have equal probability of arriving, so there is no set order in which resource types arrive. For instance, if we have two Type I engines with three personnel, and one Type I engine with four personnel, the next engine will be equally likely a Type I with three or four personnel. Based on conversations with LACoFD, there are typically fewer Type III engines (with four personnel) and Type I Engines with four personnel than there are Type I engines with three personnel. Giving all resource types an equal probability allows less common, but still used, resources to still have a considerable impact on acreage containment. Another approach would be to give all resources available equal probability of arriving, regardless of type. This approach was not considered in ACS.

- Assumptions (4), (5), (6), and (7) were provided by LACoFD. Assumption (7) is based on the propagation of fire, illustrated in Figure 18.

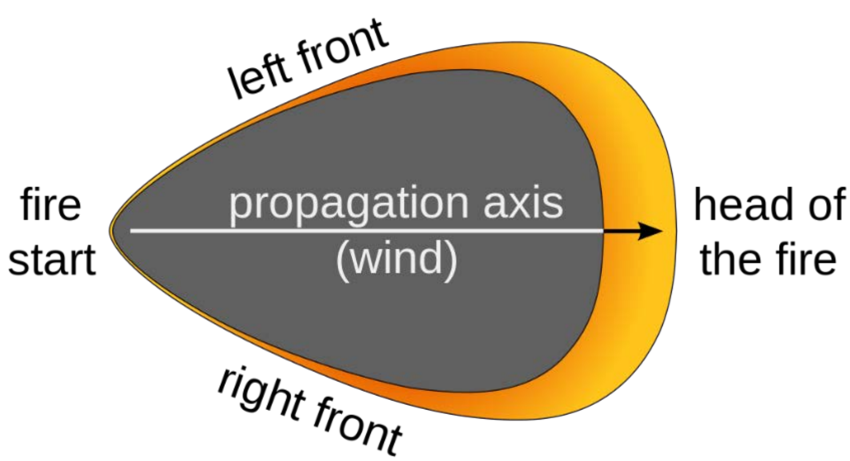


Figure 18. Fire Propagation Model. Source: Wildfire Modeling (2020).

- Assumption (8) accounts for differences in hose lay rates based on terrain. In steeper terrain, hose lay rates should be slower than those of flat terrain.

- Assumption (9) is based on LACoFD's statement that engines will sortie when water is low – not when it has run out.

- Assumption (10) was provided by LACoFD for ACS modeling, even though pumping rate could increase to 40 gpm in some cases.

- Assumption (11) ensures that the simulation only captures the impact of the resources available to a RAWS. While in practice, LACoFD may call in resources from other RAWS, this would not occur in the first hour, so it is beyond our simulated time horizon.

3. Inputs

ACS requires a resource package for each RAWS, as well as its terrain, accessibility, and sortie data. For each RAWS, LACoFD provides the minimum and maximum value for each resource. Using these values, every possible combination of resources for each RAWS has been simulated. Overall, we have simulated over 3 million packages, each for 1,000 replications.

4. Process Flow

ACS assumes a fire start in a particular RAWS has been reported. ACS can be summarized into the following steps:

1. Start;
2. Decide Duration of Current Configuration;
3. Assess Water Capacity;
4. Update Hose Lay;
5. Update Water Capacity;
6. Process Engine Arrival;

7. Return to Step 2.

The following paragraphs describe the above steps in more detail.

a. *Start*

ACS begins at time zero ($t_0 = 0$), when the first engines arrive on scene. The first engines on scene are Type VI engines (if available), water tenders (if available), and one Type I engine. Their requisite personnel are also on scene. We update water capacity and hose length to reflect the capacity and hose packs that these engines contribute. We set $t_{old} = t_0$.

b. *Decide Duration of Current Configuration*

We define the current configuration as the composition of engines and personnel currently on scene. We draw a random uniform time interval for the duration of this configuration: $t_a \sim U(2,5)$ (minutes). We set $t_{new} = t_{old} + t_a$. At this time, a new engine will arrive (if available) and the current configuration will change. Before updating the current configuration, we must process additional information: assess water capacity, update hose lay, and update water capacity.

c. *Assess Water Capacity*

At time t_{new}, we check water capacity to assess if a sortie is necessary. If so, either a water tender or Type I engine (and one requisite person) will depart the scene of the fire to retrieve water. If a sortie is already in process, and the time since the sortie began exceeds the "sortie time" of that particular RAWS, the engine will return and refill water capacity. Only one engine can sortie at a time.

After the sortie assessment, water capacity is again assessed to ensure that it remains non-negative in the interval between t_{old} and t_{new}. This capacity of water utilized in each time interval is based on the pump rate of 10 gpm per hose lay.

d. Update Hose Lay

Here, we update hose lay that occurs between t_{old} and t_{new}. However, if water capacity drops to zero during that interval, hose lay is not updated. Additionally, if progressive hose lay at time t_{new} would exceed the hose length available based on the number of available hose packs, we update hose lay to equal the hose pack length available. Otherwise, progressive hose lay lengthens according to the hose lay rates in Table 4 and the number of personnel laying hose. Table 6 shows an example of this update for six Type I engines, E1,…,E6, each with three personnel, arriving at times $t_1,\ldots,t_6$ (minutes), laying hose $H_1,\ldots,H_6$ (feet) at production rates R_p, where p is the number of personnel available.

Table 6. Hose-Lay Progress Example. Adapted from Freeman (2020a).

Event	**Time (minutes) After Dispatch**	**Engine Arriving**	**Hose-Lay Action (personnel, flank)**	**Hose-Lay Progress up to Time (feet)**
1	t_1	E1	(2, right)	$H_0 = 0$
2	t_2	E2	(4, right)	$H_1 = R_2(t_2 - t_1)$
3	t_3	E3	(4, right) (2, left)	$H_2 = R_4(t_3 - t_2) + H_1$
4	t_4	E4	(4, right) (4, left)	$H_3 = R_4(t_4 - t_3) + R_2(t_4 - t_3) + H_2$
5	t_5	E5	(6, right) (4, left)	$H_4 = R_4(t_5 - t_4) + R_4(t_5 - t_4) + H_3$
6	t_6	E6	(6, right) (6, left)	$H_5 = R_6(t_6 - t_5) + R_4(t_6 - t_5) + H_4$
7	t_7	N/A	N/A	$H_6 = R_6(t_7 - t_6) + R_6(t_7 - t_6) + H_5$

As illustrated in Table 6, as ACS progresses, two hose lays begin to form on the right and left flank of the fire. Once two hose lays have formed, personnel reinforce the hose-lay effort until the maximum “personnel on hose” capacity has been reached. At this point, any extra personnel begin constructing fire lines, further contributing to the fire containment effort. These “extra personnel” are tracked throughout each ACS run, and will be incorporated into model outputs.

e. Update Water Capacity

Here, we update water capacity that occurs between t_{old} and t_{new}. After progressive hose lay is updated, overall water capacity is subtracted by the water used in the time interval between t_{old} and t_{new}, that is, by $10 \cdot (t_{new} - t_{old})$ gallons per hose. If water capacity drops to zero in the interval between t_{old} and t_{new}, we do not update hose lay or water capacity. In this instance, we assume that, at t_{old}, we stop laying hose and using water.

f. Process Engine Arrival

If an engine has not arrived, the next engine arrives at time t_{new}. This engine is selected randomly from all Type I (with three or four personnel) and Type III engines. All types of assembled resources have equal probability of arriving. This arrival triggers additional updates:

- Personnel increases by that engine’s number of personnel.
- Water capacity increases by its arriving water capacity. And,
- Maximum hose length increases by its respective hose pack length.

If no engine is available, personnel, water capacity, and hose length do not increase. Lastly, we set $t_{old} = t_{new}$ and return to step (2).

5. Outputs

We simulate 30 minutes after the arrival of the first engine; that is, the simulation concludes when $t_{new} = 30$. Even though the simulation could be extended to include a longer horizon, our goal here is to model initial attack. This is consistent with one of LACoFD’s goals: to rapidly suppress fires and prevent them from expanding beyond 10 acres, which often occurs in a very short, 20- to 30-minute time span. At the conclusion of each simulation run, an “acreage contained in 30 minutes” value is provided as an output. For more insight, acreage containment values can also be gathered throughout the duration of the simulation.

The area of containment is determined using the perimeter of hose laid around a 45-degree sector of a circle, representing the right and left flanks closing toward each other. Equation (3) displays the calculation of this area, where H is the feet of hose laid in 30 minutes.

$$Area\ of\ \ Containment = \frac{\pi}{8}R^2 \text{, where } R = \frac{H}{2+\frac{\pi}{4}} \tag{3}$$

This area is converted from square feet to acres. LACoFD provided Figure 19 to illustrate this calculation and depict the hose lay length necessary to surround a 10-acre fire.

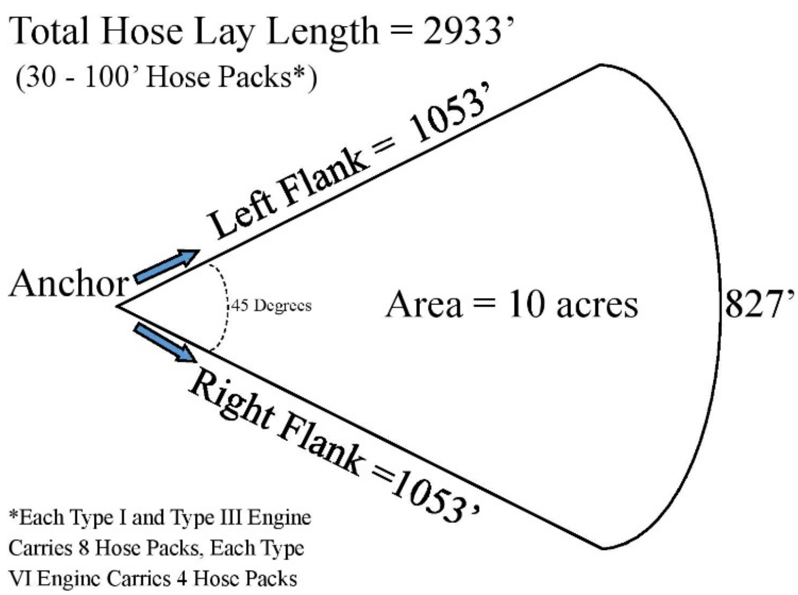


Figure 19. Area of Containment. Source: Freeman (2020).

For a given resource package, the simulated area contained is averaged across 1,000 replications and provided as an output. We are also interested in the number of “extra personnel” (described later in this section) for each package, as we increase acreage containment based on this value. Replications may have varying numbers of extra personnel depending on how many three- and four- person engines arrive, so we average this value across 1,000 replications and provide it as an output for each package. Additionally, ACS introduces a new resource: the “hand crew.” Each hand crew consists of a bus holding 12 hand-crew members, as well as one FFS. Crew members act as “extra personnel,” and are included in the average value at the end of each simulation run.

Subsequently, we allow adjustments to the acreage containment output from ACS. We enact these increases to help quantify the value of resources that do not contribute directly to the hose-lay effort, but still contribute to overall acreage containment. Let A denote RAWS accessibility and S denote RAWS sortie time. We increase simulated containment as follows:

- By 0.5% for every extra person on scene;
- By $(10 - A)$% for every Type VI engine on scene; and,
- By $(0.1 \cdot S)$% for every water tender on scene.

The rationale for increasing acreage containment is as follows: Extra personnel do not lay hose, but they are still crucial to the fire containment effort. Likewise, the Type VI engine is not designed to specifically contribute to the main hose-lay effort. The Type VI is essential in the response to incidents that are less accessible, as it is the most maneuverable of the engines. Thus, Type VI engines’ contribution to acreage contained is a function of accessibility.

Finally, in just a 30-minute time period, the value of the water tender is not apparent, as in most cases water is not depleted. A water tender is more useful in RAWS that have a larger sortie time, which corresponds to difficult terrain and low accessibility. In instances where the sortie time is short, a water tender is not as essential, as regular engines can retrieve water and return to the fire site in minimal time. With long sortie times, engines will be gone for extended periods of time, meaning refills are not as easy or quick. A water tender is beneficial in these scenarios, and thus, its contribution to acreage contained is a function of sortie time.

These notional increases are not performed in ACS itself. Rather, they are performed on completed ACS outputs. This allows us to test different adjustments without rerunning ACS. In the following section, "30-minute acreage containment" refers to the value generated after these adjustments.

6. Regression on Outputs

We develop a multiple linear regression to estimate acreage containment via a metamodel of ACS for any package and RAWS. The benefit of this is twofold: First, the simulated packages are based on the minimum and maximum resource values provided by LACoFD, but these values may change. The approximating metamodel can provide estimated containment without the need to simulate those packages. Second, even if the acreage containment values for the three million simulated packages is stored, accessing these values for a typical optimization (including several hundred thousand packages) may take several minutes. A functional approximation is much faster to compute.

We use individual resources as predictors and 30-minute acreage containment as the response. With zero resources, acreage containment should be zero, so regression through the origin is utilized. Also, no interactions are incorporated into the models, as this results in some terms having non-intuitive negative coefficients to compensate for other terms. Moreover, our meta-models have sufficiently low root mean square error (RMSE, see e.g. Faraway 2016) values, ranging from 2.46 to 5.36 acres for all 21 RAWS.

The generic multiple linear regression model for each RAWS carries the form shown in Equation (4), where: a_{kw} denotes the acreage containment value for package k in RAWS w; x_{kws} denotes the number of assembled (engine and its personnel) resources of type s in package k for RAWS w; and $\widehat{\beta}_{ws}$ is the regression coefficient for resource type s for RAWS w.

$$a_{kw} = \sum_{s} \widehat{\beta}_{ws} x_{kws} \tag{4}$$

Table 7 displays these regression coefficients. For all regressions, the probability value (*p*-value) for each predictor is below 2.2^{-16}. If we see a *p*-value below 0.05, we infer that there is a relationship between that predictor and the response (James et al. 2017). We conclude that all predictors for all regressions are significant. We also display the minimum absolute residual, RMSE, and maximum absolute residual for each regression.

Although RMSE values are acceptable for all RAWS, we note that some RAWS have high maximum absolute residuals. For instance, the regression for Cheseboro has a RMSE of under 5 acres, but a maximum absolute residual of 27.3 acres. Fortunately, these can be considered outliers as their frequency is very low. For example, for Cheseboro, only 10 observations have maximum absolute residuals of over 25 acres (a relative frequency of 0.016%), and only 886 residuals are above 15 acres (1.44%). The next section introduces an optimization model that uses the regression estimates. We note such optimization model could be improved by overriding the abovementioned outliers with the original ACS values, but this research does not explore that option.

Table 7. ACS Regressions

RAWS w	$\widehat{\beta}_{ws}$ Assembled Resource s: Type I Engine with Three Personnel	Type I Engine with Four Personnel	Type III Engine with Four Personnel	Type VI Engine with One Personnel	Type VI Engine with Two Personnel	Water Tender with One Personnel	Bus with Hand-Crew and One Personnel	Minimum Absolute Residual	RMSE	Maximum Absolute Residual
Santa Fe Dam	1.10	1.19	0.32	0.73	2.62	0.82	2.06	4.48e-6	3.56	11.74
Henninger Flats	1.24	1.54	0.46	2.23	4.11	1.73	1.43	8.05e-5	2.83	9.77
Claremont	1.46	1.66	0.57	1.47	3.94	1.27	2.20	4.27e-6	4.24	14.82
Whittier	0.42	0.41	0.21	0.43	1.90	0.74	1.67	2.39e-6	2.46	7.84
San Rafael	2.39	2.87	2.17	1.00	2.49	0.85	1.39	7.17e-5	4.71	23.32
Tonner Canyon	1.41	1.66	0.45	2.25	4.28	1.65	1.66	9.11e-5	3.16	10.19
Cheseboro	1.90	2.37	1.69	1.72	3.22	1.17	1.18	9.40e-5	4.87	27.32
Malibu	1.74	2.16	1.40	1.81	3.45	1.44	1.47	3.71e-5	3.82	24.14
Beverly Hills	1.14	1.24	0.44	0.98	2.88	1.10	1.78	3.15e-5	3.20	10.75
Leo Carrillo	2.71	3.27	2.64	1.20	2.73	0.61	1.01	1.47e-3	5.16	20.92
Malibu Canyon	1.25	1.55	0.61	2.05	3.88	1.66	1.42	1.13e-4	2.78	9.71
Topanga	2.48	3.02	2.37	1.09	2.52	0.70	1.02	1.12e-4	4.69	19.86
Saugus	1.61	1.88	0.51	0.97	3.02	1.03	1.84	7.73e-6	3.47	11.43
Acton	2.40	2.89	2.21	1.17	2.71	0.87	1.37	5.61e-5	4.86	24.47

$\widehat{\beta}_{ws}$								**Minimum Absolute Residual**	**RMSE**	**Maximum Absolute Residual**
RAWS *w*	**Assembled Resource *s***									
	Type I Engine with Three Personnel	**Type I Engine with Four Personnel**	**Type III Engine with Four Personnel**	**Type VI Engine with One Personnel**	**Type VI Engine with Two Personnel**	**Water Tender with One Personnel**	**Bus with Hand-Crew and One Personnel**			
Del Valle	2.48	3.02	2.37	1.09	2.52	0.70	1.02	2.32e-4	4.69	19.86
Newhall Pass	1.28	1.55	0.64	1.88	3.50	1.75	1.70	5.58e-5	3.48	11.82
Camp 9	1.72	2.18	1.54	1.77	3.37	1.29	1.18	1.77e-4	3.85	23.13
Whitaker I-5	1.97	2.50	1.75	1.66	3.18	1.09	1.04	1.49e-4	4.53	23.33
Poppy Park	2.72	3.28	2.59	1.38	3.22	0.74	1.42	3.70e-4	5.35	25.08
Saddleback	2.62	3.17	2.34	1.91	4.13	1.01	1.80	4.61e-5	5.36	28.73
Lake Palmdale	1.37	1.57	0.61	2.45	5.28	1.24	2.14	1.04e-5	4.01	14.33

D. OPTIMIZATION MODEL

In this section, we develop AOM with Simulation (AOMS). AOMS is a modified version of the legacy AOM (Scholz 2019) that incorporates ACS inputs and a number of modeling enhancements. These enhancements contribute to more flexible solutions and (empirically) faster model runs. AOMS seeks to optimally determine how to relocate LACoFD resources in order to minimize a risk assessment function. This risk is expressed in terms of an expected loss that balances population density and acreage containment across all RAWS.

1. Specifications

AOMS is designed to provide LACoFD with each RAWS' probability of fire, estimated 30-minute acreage containment, and recommended augmentation plan. The following sub-sections provide a description of the model structure.

a. Firefighting Resources

AOMS utilizes two different types of resources: unassembled and assembled. Unassembled resources are divided into personnel and engine resources. Unassembled resources are also divided into internal and external. Internal resources are those that are staffed daily (in an on-duty status). These resources are also referred to as frontline. External resources are those that are marked on reserve for the day. Table 8 displays personnel resources, alongside the off-duty availability of each personnel type and the daily cost of augmenting by calling them up. Table 9 displays engine resources, alongside the per-mile cost of moving each engine type. Personnel resources and engine resources are combined to create assembled resources, as displayed in Table 10.

Table 8. Personnel Resource Data

	Captain (CA)	Fire Fighter Specialist (FFS)	Fire Fighter (FF)
Number of Off-Duty Available in LACoFD	152	141	166
Off-Duty Daily Cost	$1,848	$1,560	$1,320

Table 9. Engine Resource Data

	Type I Engine (T_I)	Type III Engine (T_III)	Type VI Engine (T_VI)	Water Tender (WT)	Bus (BUS)
Per-mile Cost of Movement	$0.89	$0.57	$0.44	$0.89	$0.80

Table 10. Assembled Resources and Their Composition

	T_I with 3 Personnel (T_I_3)	T_I with 4 Personnel (T_I_4)	T_III with 4 Personnel (T_III_4)	T_VI with 1 Personnel (T_VI_1)	T_VI with 2 Personnel (T_VI_2)	WT with 1 Personnel (WT_1)	Crew (CREW_1)
Composition	T_I staffed with one CA, one FFS, and one FF	T_I staffed with one CA, one FFS, and two FFs	T_III staffed with one CA, one FFS, and two FFs	T_VI staffed with one FF	T_VI staffed with one FF and one CA	WT staffed with one FFS	BUS staffed with twelve crew members and one FFS

b. Transfer of Firefighting Resources

AOMS allows unassembled resources (both internal and external) to be transferred among RAWS, and ultimately combined to create packages of assembled resources. The flow of internal engines and personnel, and the flow of external engines, is assumed to occur between individual RAWS sub-areas. That is, all fire station data are aggregated at the RAWS level (because our fire predictions are only established at that level). External personnel account for off-duty staff being called up to a RAWS. AOMS could handle these personnel with origin at a particular RAWS or climatic zone, but LACoFD only has this information available for all of LAC.

c. Firefighting Resource Costs

AOMS accounts for the costs of engine transfers, as well as the cost of calling up off-duty personnel. The cost of engine transfers is based on the average gas mileage in miles per gallon for each engine type. LACoFD provided these values, and using average gas prices in LAC, the costs in Table 9 result. LACoFD also provided notional distances between RAWS sub-areas. Personnel costs are based on the off-duty personnel costs displayed in Table 8. These costs are calculated using the overtime, hourly rate for each personnel type and a 24-hour augmentation schedule (Scholz 2019). Calling up off-duty personnel typically constitutes the majority of AOMS' costs.

d. Augmentation Requirements

By policy, the determination for augmentation of a RAWS sub-area is based on the BIR. To accommodate this, RAWS are divided into two categories: RAWS that can receive resources and RAWS that can give resources.

Standard practice establishes that a RAWS that has a BIR at or above one can receive (but not give) resources. Additionally, any RAWS within a climactic zone whose average BIR exceeds one can receive resources. A RAWS with a BIR below one can give (but not receive) resources, unless it belongs to a zone whose average BIR is greater than one (in which case that RAWS can both give and receive resources). Additionally, there are instances where LACoFD may decide to override these default rules and select which RAWS can give and/or receive resources based on expert judgement. Thus, we generalize the idea to allow a RAWS to be in both categories simultaneously if LACoFD chooses so. AOMS uses these criteria to efficiently build candidate resource packages, as described below.

e. Candidate Resource Packages

For each RAWS, AOMS optimizes the number of the seven types of assembled resources, together called a resource package. Candidate resource packages depend on the minimum, maximum, and baseline number of assembled resources specified for each RAWS, and on whether or not the RAWS can give or receive resources.

The minimum number of resources describes the minimum quantity of resources that must remain within each RAWS. These data are based on LAC contracts requiring fire stations to keep a certain number of resources on hand in case a structure fire occurs (Scholz 2019). LACoFD has provided minimum resource values by station, which we aggregate to reflect minimum resources by RAWS.

The maximum number of resources by RAWS are also provided by LACoFD, and are based on maximum parking spaces and support facilities. These upper bounds help AOMS generate a reasonable, finite number of resource packages.

The baseline number of resources describes the number of resources regularly positioned within each RAWS. These values are provided by station from LACoFD and are aggregated to reflect baseline resources by RAWS. These resources are also provided in unassembled format.

Candidate resource packages contain a component for each individual assembled resource. For RAWS that can only receive resources, these components range from the baseline to the maximum of that assembled resource. This eliminates the option for that RAWS to give resources, and efficiently creates fewer packages for AOMS to process. Similarly, for RAWS that can only give resources, these components range from the minimum to the baseline of that assembled resource. For RAWS that can both give and receive resources, these components range from the minimum to the maximum of that assembled resource. Minimum, baseline, and maximum values are aggregated for T_I_3s and T_I_4s; the same occurs for T_VI_1s and T_VI_2s.

AOMS iteratively creates every possible package based on the guidelines above. In many scenarios, the resulting number of resource packages requires a lot of processing power and memory when building the optimization model. We seek a decision support system that is reasonably responsive, and want to recommend solutions within minutes, not hours. To alleviate this problem in instances where processing power and/or memory are limited, LACoFD is able to set a maximum number of candidate resource packages to be considered for each RAWS. AOMS will then remove packages for each RAWS in order not to exceed this maximum number. Candidate resource packages are removed based on Euclidean distance from the baseline package, represented as a vector. Packages that are furthest from the baseline are removed. We note that reducing the number of packages in this way is a restriction that may result in degradation of optimality.

f. Loss Function

We incorporate a loss function *L* into the objective function of AOMS in order to allocate resources most effectively. First, let a_w be the estimated 30-minute acreage containment produced by ACS at RAWS *w* (Note: For exposition's sake, we have dropped sub-index k from a_{kw}; thus, here a_w refers to the specific containment for the final chosen package at RAWS *w*.). Also, let ρ_w be the population density of RAWS *w* and $F(a_w)$ be a decreasing function of a_w. We define the loss function *L* as the expected value of $\rho_w F(a_w)$ across all RAWS, that is:

$$L = \sum_{w \in W} p_w \rho_w F(a_w) \quad , \tag{5}$$

where p_w is the probability of fire in RAWS *w*.

Given $F(a_w)$ is a decreasing function, minimizing *L* encourages decisions that increase a_w. For example, in instances of RAWS *w* where identical resources contribute similarly to containment, a_w, minimizing *L* encourages decisions that send more resources to RAWS *w* with higher values of $p_w \rho_w$.

Note that if we had just considered a linear function of a_w in order to maximize $\sum_{w \in W} p_w \rho_w a_w$, the result would be extremely skewed toward RAWS with a high $p_w \rho_w$ coefficient. Specifically, the single RAWS with highest coefficient would receive as many resources as it physically could (before any other RAWS does); then, the RAWS with the second-highest coefficient would follow suit; and so on. Even though not being explicitly maximized, $\sum_{w \in W} p_w \rho_w a_w$ is an important statistic to report. Given $\rho_w a_w$ is in the unit "persons per 30 minutes," it can be interpreted as the population equivalent to an area that the pre-positioned resources can contain in 30 minutes, in RAWS w. For exposition, we refer to it as estimated "persons protected per 30 minutes." By extension, when referring to all RAWS, we refer to $\sum_{w \in W} p_w \rho_w a_w$ as expected persons protected in 30 minutes. Similarly, we shall also refer to $\sum_{w \in W} p_w a_w$ as the expected acreage containment.

By defining *L* as in (5), we still encourage sending resources to RAWS with higher $p_w \rho_w$ coefficients, but also balance the apportion of resources among all RAWS. The shape of that balance depends on our choice for $F(a_w)$. For this research, we use $F(a_w) = a_w^{-1}$, but note that $F(a_w)$ could be chosen from general families of decreasing functions such as $F(a_w) = a_w^{-q}$ for $q>0$ or $F(a_w) = q^{-a_w}$ for $q>1$, among others. Each of these would produce a different distribution of resources depending on *q*.

g. *Desired Package Guidance*

AOMS allows LACoFD to test a specific resource package, or any of its individual components, for any RAWS. To accomplish this, we incorporate a new term into the objective function of AOMS that penalizes Euclidean distance from the chosen package for each RAWS to the desired one. Additionally, we allow LACoFD to provide a weight, also by RAWS, indicating how important adherence to the desired package is.

2. Indices and Sets

E, set of engine types, for $e \in E = \{\text{TI, TIII, TVI, WT, BUS}\}$;

P, set of personnel types, for $p \in P = \{\text{CA, FFS, FF}\}$;

S, set of assembled resource types, for $s \in S = \{\text{T\_I\_3, T\_I\_4, T\_III\_4, T\_VI\_1, T\_VI\_2, WT\_1, CREW\_1}\}$;

W, set of RAWS, for $w, w' \in W = \{\text{Saugus, Whittier, ...}\}$;

W^+, W^-, subsets of RAWS that can receive or give resources, respectively.

3. Parameters [Units]

n_{we}^{E}, number of baseline engines of type $e \in E$ available in RAWS $w \in W$. Remark: This parameter is the sum of the active baseline engines for the RAWS and external engines contributed by the stations in the RAWS (that changes daily according to engine reserve status) [engines];

n_{wp}^{P}, number of baseline, active personnel of type $p \in P$ in RAWS $w \in W$ [persons];

n_{p}^{O}, total number of off-duty personnel of type $p \in P$ available [persons];

$c_{ww'e}^{E}$, daily cost of moving one engine of type $e \in E$ from RAWS w to w', for $w, w' \in W$ [$/engine];

c_{p}^{O}, daily cost of calling up one off-duty personnel of type $p \in P$ [$/person];

b, daily budget for moving engines and calling up off-duty personnel [$];

ε_C, small tie-breaker parameter to ensure surplus budget is not spent unnecessarily. We use a variety of values such as from $\varepsilon_C = 10^{-10}$ (cost is not relevant) to $\varepsilon_C = 10^{-1}$ (cost is important and should be kept low);

ε_P, small tie-breaker parameter to discourage unnecessary transfers of internal personnel. Moving internal personnel is free, and this parameter ensures that personnel are not transferred in excess. We use $\varepsilon_P = 10^{-3}$;

ε_U, small tie-breaker parameter to discourage the selection of packages in which there are unused on-duty personnel. We use $\varepsilon_U = 10^{-3}$;

ε_w^d, weight parameter specific to RAWS $w \in W$ that is used to encourage the model to select a solution that is close to a desired solution, if one is nominated. A typical value is $\varepsilon_w^d \in [1, 5]$;

p_w, probability of fire in RAWS $w \in W$ (calculated by logistic regression model);

ρ_w, population density for RAWS $w \in W$ [persons/acre].

4. Derived Sets and Data [Units]

K_w, set of candidate packages of assembled resources for RAWS *w*, for $k \in K_w$. Each package is a tuple of $|S|$ components; each component indicates how many of each type of assembled resource $s \in S$ there are in the package. Each assembled resource $s \in S$ requires a number of engines $e \in E$ and personnel $p \in P$, which is also specified separately;

m^E_{kwe}, number of engines of type $e \in E$ in package $k \in K_w$ for RAWS $w \in W$ [engines];

m^P_{kwp}, number of personnel of type $p \in P$ in package $k \in K_w$ for RAWS $w \in W$ [persons];

a_{kw}, estimated 30-minute acreage containment for package $k \in K_w$ in RAWS $w \in W$. This is calculated using ACS or its regression meta-model [acres/30 min];

$F(a_{kw})$, decreasing function, representing the partial loss for assigning package $k \in K_w$ to RAWS $w \in W$. We use $F(a_{kw}) = a_{kw}^{-1}$ [30 min/acre];

d_{kw}, Euclidean distance between package $k \in K_w$ for RAWS $w \in W$ and the desired package for RAWS w. If no package is specified for RAWS w, the distance for all packages k equals zero.

5. Decision Variables [Units]

Y_{kw}, 1 if package $k \in K_w$ is chosen for RAWS $w \in W$, and 0 otherwise;

$X^E_{ww'e}$, number of engines of type $e \in E$ transferred from RAWS w to w', for $w \in W^-, w' \in W^+$ [engines];

$X^P_{ww'p}$, number of active personnel of type $p \in P$ transferred from RAWS w to w', for $w \in W^-, w' \in W^+$ [persons];

O_{wp}, off-duty personnel of type $p \in P$ called up to RAWS $w \in W$ [persons];

P_{wp}, unused personnel of type $p \in P$ left idle (i.e., not staffed) at RAWS $w \in W$ [persons];

C, daily cost of the pre-positioning assignment [$].

6. Formulation

$$\min_{Y,X^E,X^P,O,P,C} \quad \sum_{w\in W}\sum_{k\in K_w} p_w\rho_w F(a_{kw})Y_{kw} + \\ \varepsilon_C C + \varepsilon_P \sum_{w\in W^-}\sum_{w'\in W^+}\sum_{p\in P} X^P_{ww'p} + \varepsilon_U \sum_{w\in W}\sum_{p\in P} P_{wp} + \sum_{w\in W}\sum_{k\in K_w} \varepsilon^d_w d_{kw} Y_{kw} \tag{6}$$

Subject to:

$$\sum_{k\in K_w} Y_{kw} = 1, \qquad \forall w\in W \tag{7}$$

$$\sum_{k\in K_w} m^E_{kwe} Y_{kw} \le n^E_{we} - \sum_{w'\in W^-} X^E_{w'we|w\in W^+} + \sum_{w'\in W^+} X^E_{ww'e|w\in W^-}, \ \forall w\in W, e\in E \tag{8}$$

$$\sum_{w'\in W^+} X^E_{ww'e} \le n^E_{we}, \ \forall w\in W^-, e\in E \tag{9}$$

$$\sum_{k\in K_w} m^P_{kwp} Y_{kw} = n^P_{wp} - \sum_{w'\in W^-} X^P_{w'wp|w\in W^+} + \sum_{w'\in W^+} X^P_{ww'p|w\in W^-} + O_{wp|w\in W^+} - P_{wp}, \ \forall w\in W, p\in P \tag{10}$$

$$\sum_{w\in W^+} O_{wp} \le n^O_p, \qquad p\in P \tag{11}$$

$$C = \sum_{w\in W^-}\sum_{w'\in W^+}\sum_{e\in E} c^E_{ww'e} X^E_{ww'e} + \sum_{w\in W^+}\sum_{p\in P} c^O_p O_{wp} \tag{12}$$

$$0 \le C \le b \tag{13}$$

$$Y_{kw} \in \{0,1\}, \qquad \forall k\in K_w, w\in W \tag{14}$$

$$X^E_{ww'e}, X^P_{ww'p}, O_{w'p} \ge 0 \text{ and integer}, \qquad \forall w\in W^-, w'\in W^+, e\in E, p\in P \tag{15}$$

$$P_{wp} \ge 0 \text{ and integer}, \qquad \forall w\in W \tag{16}$$

7. Constraint Descriptions

A brief explanation of the mathematical formulation follows:

- Equation (6) is the objective function of the optimization model: the objective expresses the expected total loss across all RAWS, while incorporating other tie-breaking and penalty terms. These other parameters include: a cost tie-breaking term, a penalty on internal personnel movement, a penalty on unused on-duty personnel, and a penalty on distance from LACoFD's desired package(s). In addition to the objective minimized, we report expected "persons protected in 30 minutes" and expected "acreage containment in 30 minutes" values, which equate to $\sum_{w \in W} \sum_{k \in K_w} p_w \rho_w a_{kw} Y_{kw}$ and $\sum_{w \in W} \sum_{k \in K_w} p_w a_{kw} Y_{kw}$, respectively.

- Each partition constraint (7) ensures that each RAWS $w \in W$ receives exactly one candidate resource package.

- Each constraint (8) ensures the conservation of flow for engine resources. For each engine $e \in E$ and RAWS $w \in W$, the number of engines available after receiving and/or giving resources, must be greater than or equal to the total number of engines required for the candidate resource package selected. In addition, each constraint (9) ensures no RAWS gives more engines than it has. This prevents a RAWS from receiving and transferring the same type of engine. Even though such solutions would be suboptimal, the constraint eliminates those solutions from being feasible.

- Each constraint (10) ensures the conservation of flow for personnel resources. For each personnel type $p \in P$ and RAWS $w \in W$, the number of personnel available after receiving and/or giving resources (including off-duty) must be greater than or equal to the total number of personnel required for the candidate resource package selected. The number of on-duty personnel not assigned to the selected candidate resource package is added as a slack variable, making this constraint an equality.

- Each constraint (11) ensures that for each personnel type $p \in P$, the total number of off-duty personnel called up does not exceed the total number of off-duty personnel available.

- Constraints (12) and (13) relate to the cost of an AOMS solution. Constraint (12) defines the cost C as the sum of all engine transfer costs added to the sum of all off-duty personnel costs. Constraint (13) requires that this cost be less than the budget provided by LACoFD.

- (14)-(16) establish the decision variable domains.

AOMS is currently implemented using the Python computer language and Pyomo optimization software (Hart et al. 2011, 2017). The optimization uses CPLEX as the solver engine (IBM 2020). AOMS contains up to 300 constraints, and if no candidate resource package limits are set, it can contain over 3 million variables depending on RAWS BIR values. By limiting the number of candidate packages to, say, 20,000 for each RAWS, AOMS is, on average, solved within 1 minute using an optimality gap (the relative difference between the best solution found and the best-known bound on the optimal solution) of 1%.

IV. ANALYSIS

A. INTRODUCTION

This chapter presents an analysis of AOMS results and overall performance. We delivered AOMS to LACoFD in October of 2020, and LACoFD began using the program daily, saving results for analysis, and providing feedback on their progress and any problems they encountered. An improved interface allows for easy data input and parameter control, and makes a variety of clean, intuitive outputs available, suitable for view by senior policy makers.

To input the data and parameters necessary to run AOMS, LACoFD utilizes an Excel workbook. Inputs include, but are not limited to, budget, WIMS data, desired packages, maximum packages, penalty parameters, and baseline, minimum, and maximum resource values. Figure 20 displays the case information input to this workbook. LACoFD inputs the date and objective-function related parameters: penalties ε_P and ε_U, and a range of "cost relevance" levels, c_r, between 0 and 10. Each cost relevance level is used to set the cost penalty in the objective function of AOMS: $\varepsilon_C = 10^{-(10-c_r)}$. AOMS will produce a solution for every cost relevance between the lowest and highest levels, in increments of the cost-relevance step value. This can provide LACoFD with a diverse set of solutions for each day. Regardless of the cost-relevance level, all solutions are constrained not to exceed the budget, b, also inputted in this spreadsheet.

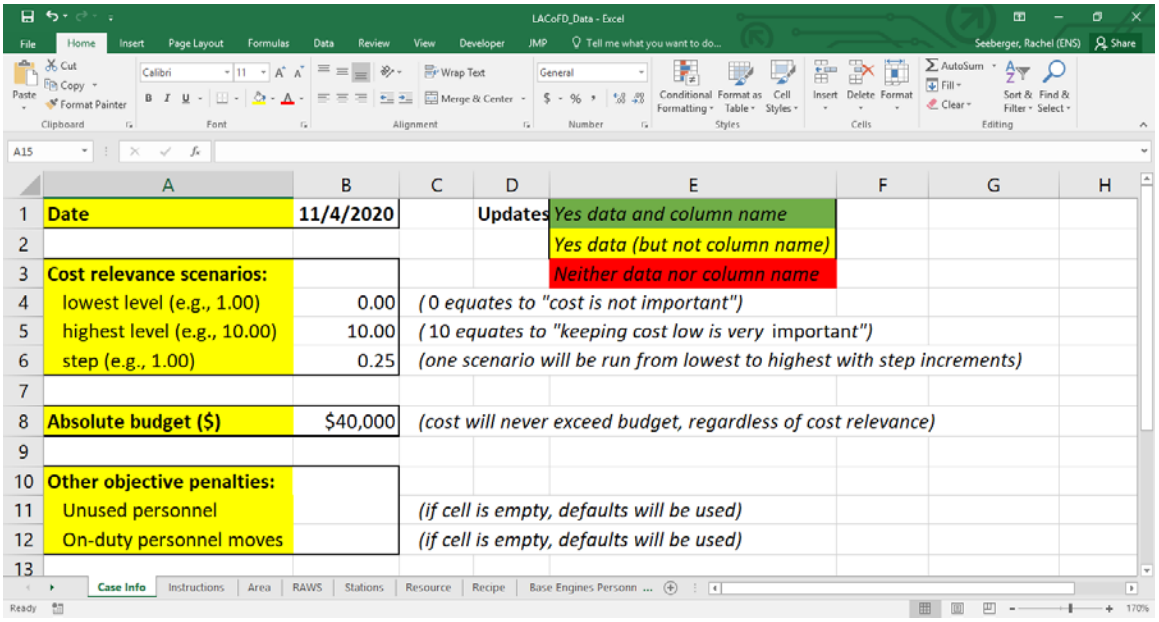


Figure 20. Case Information Input

AOMS' outputs are automatically saved to several Excel workbooks: one workbook for every cost relevance scenario, and a summary workbook. Output by scenario files reveal: an overview of the solution; a breakdown of the objective function and cost; an overall solution summary; detailed engine and personnel transfers; and, an individual synopsis of each RAWS' solution.

Figure 21 illustrates the overview tab of an output file. This tab provides the date, budget, and a cost breakdown of AOMS' solution. Figure 22 displays an example objective function breakdown tab. This tab presents the expected persons protected in 30 minutes of AOMS' solution, as well as a complete summary of objective function terms. Figures 23 and 24 display the engine and personnel transfer tabs, respectively. The entries in each tab contain tuples representing the transfer of engines or personnel. The tuple elements denote individual resources being transferred, and at the bottom of each tab is a legend decoding them. Finally, Figure 25 presents an individual RAWS solution. In an AOMS output file, there is a tab for each RAWS solution. Each tab provides a RAWS' final resource package, as well as other explanatory weather, solution, and resource transfer data.

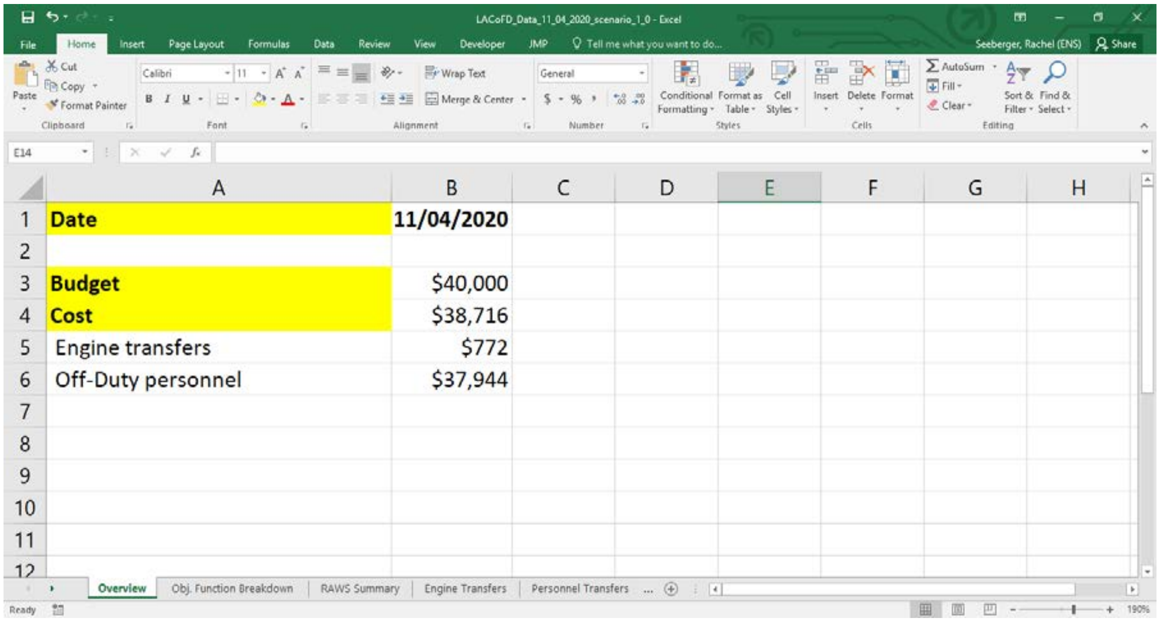
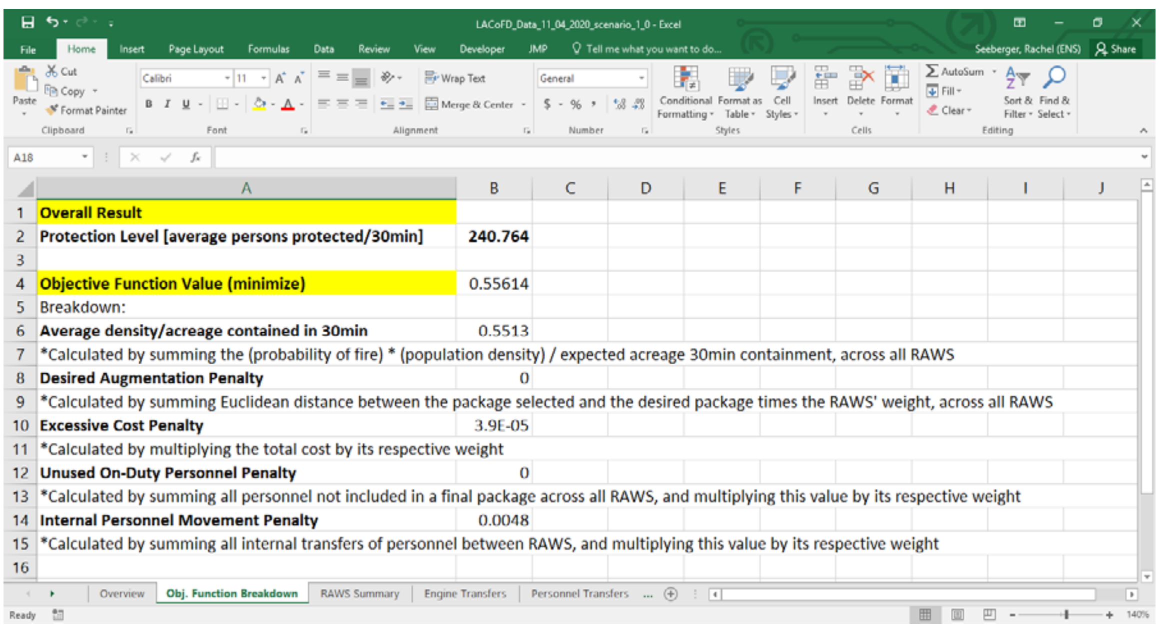
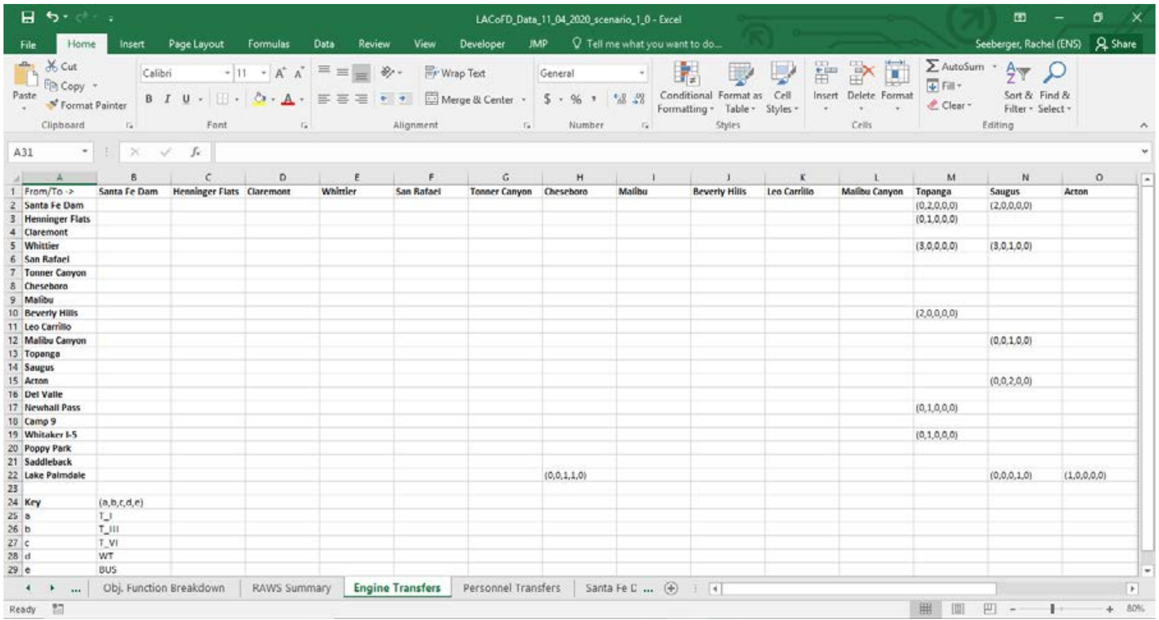


Figure 21. Overview Example



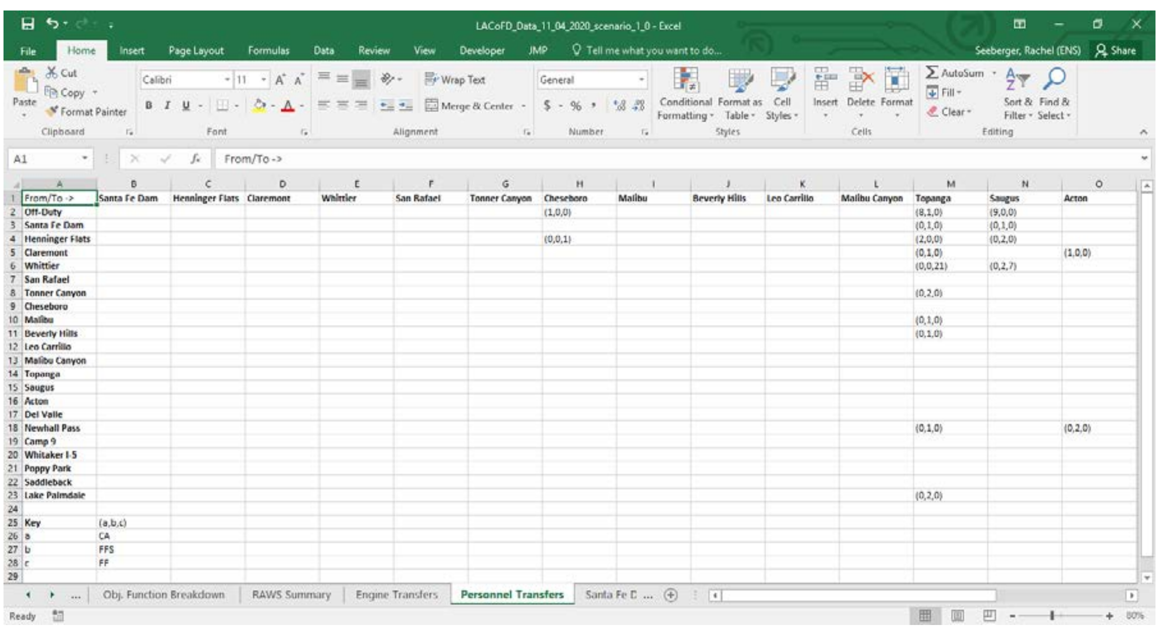
The objective function value that AOMS minimizes is the sum of five terms. In addition, we report an overall result in terms of expected persons protected in 30 minutes.

Figure 22. Objective Function Breakdown Example



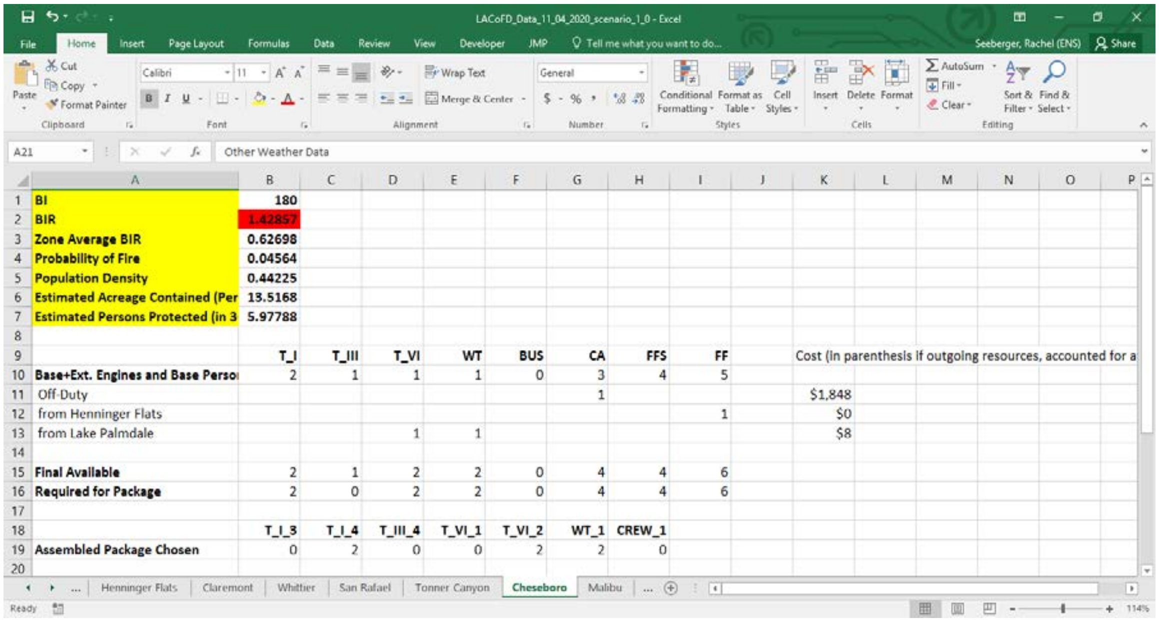
Five types of rolling equipment (engine Types I, III, and VI, water tenders, and buses) can be transferred among RAWS. In this example, Santa Fe Damn sends two Type III engines to Topanga, and two Type I engines to Saugus.

Figure 23. Engine Transfers Example



Three types of personnel (captains, firefighter specialists, and firefighters) can be transferred among RAWS, or sent to a RAWS from off-duty status. In this example, Cheseboro receives one off-duty captain, and one additional firefighter from Henninger Flats.

Figure 24. Personnel Transfers Example



The figure shows Cheseboro RAWS results. The AOMS-estimated probability of fire is approximately 4.5%, and AOMS chooses a resource package that is capable of protecting an acreage equivalent of 6 people in 30 minutes. Cheseboro receives off-duty personnel, and other personnel and engine transfers, costing $1,856. These are combined with the original baseline resources into two T_I_4, two T_VI_2, and two WT_1 assembled resources.

Figure 25. RAWS Solution Example

B. AOMS USE DURING FALL 2020 SEASON

Using these new input and output files, LACoFD began running AOMS in October of 2020. Table 11 shows AOMS' solutions for the week October 29 - November 4. Each solution used a daily budget of $20,000; however, in all cases, this budget turned out to be nonbinding. Between October 29 and November 4, very few RAWS had BI above BIT, and weather was predominantly cold and wet, so augmentation and costs were minimal. Table 11 shows only the augmented RAWS. For any RAWS in which BI did not exceed BIT, LACoFD performed a manual override to allow augmentation. We use the default values for ε_P and ε_U . No fires occurred on these dates.

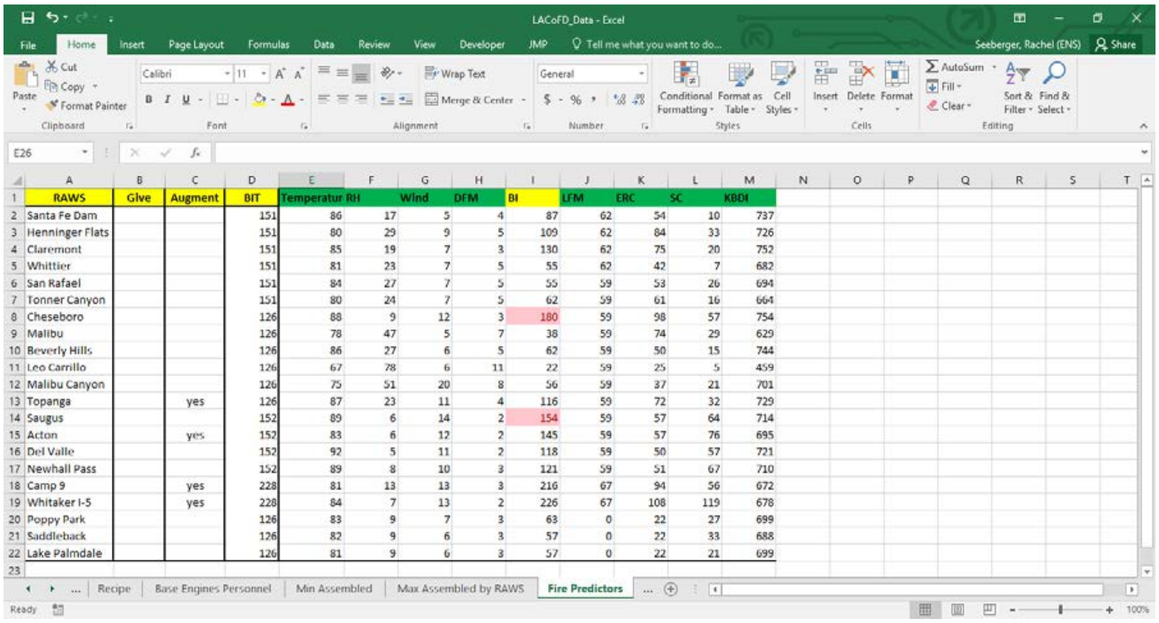
Table 11. AOMS Augmentation Results for Oct. 29 – Nov. 4 2020

<u>Date</u> 2020	RAWS	Total Number of Pre-Positioned Resources	BI > BIT	Estimated 30-Minute Acreage Containment	ε_C	Cost of Aug.
Oct. 29	Cheseboro	(1,1,0,3,0,2,0)	No	11.8	10^{-6}	$490
	Topanga	(0,5,5,5,0,2,0)	No	33.8		
	Whitaker I-5	(0,1,0,2,0,2,0)	No	8.0		
Oct. 30	Cheseboro	(0,2,4,3,0,2,0)	No	19.0	10^{-6}	$309
	Acton	(3,0,0,1,0,2,0)	No	10.1		
	Whitaker I-5	(0,2,1,1,0,2,0)	No	10.6		
Oct. 31	Cheseboro	(3,0,1,1,0,2,0)	No	11.5	10^{-4}	$449
	Topanga	(5,0,3,5,0,2,0)	No	26.4		
	Acton	(2,0,0,1,0,2,0)	No	7.7		
	Whitaker I-5	(1,0,3,1,0,2,0)	No	11.0		
Nov. 1	Cheseboro	(3,1,6,1,0,2,0)	Yes	22.3	10^{-4}	$332
	Acton	(1,1,0,2,0,2,0)	No	9.4		
	Whitaker I-5	(2,0,3,0,0,2,0)	No	11.4		
Nov. 2	Cheseboro	(7,0,6,1,0,2,0)	Yes	27.5	10^{-4}	$335
Nov. 3	Cheseboro	(0,7,6,1,0,2,0)	Yes	30.8	10^{-4}	$335
Nov. 4	Cheseboro	(2,1,1,1,0,2,0)	Yes	11.9	10^{-4}	$271
	Topanga	(0,2,5,0,0,1,0)	No	18.6		
	Saugus	(0,7,2,1,0,3,0)	Yes	18.2		
	Acton	(2,0,0,2,0,2,0)	No	8.9		
	Camp 9	(0,2,0,0,0,1,0)	No	5.7		
	Whitaker I-5	(0,1,1,0,0,0,0)	No	4.3		

The "Total Number of Pre-Positioned Resources" indicates AOMS' chosen package. A 7-tuple indicates the number of resources of each type: (T_I_3, T_I_4, T_III_4, T_VI_1, T_VI_2, WT_1, CREW_1). Associated "Estimated 30-Minute Acreage Containment" is provided by ACS.

Table 11 reveals that on only four out of seven days, a RAWS had a BI that exceeded its BIT. In many instances, LACoFD overrode the BIR augmentation requirement, and allowed RAWS with a BI below BIT to receive resources. This manual override is accomplished using a new feature in the LACoFD input file. Figure 26 displays the input interface for November 4, 2020 WIMS data. The user has the ability to override AOMS presets (based on BIR) and manually decide which additional RAWS may receive and/or give resources. Additionally, in this tab, if a RAWS BI exceeds its BIT, that RAWS

BI is highlighted red. For example, we see that Cheseboro and Saugus had BIs above their respective BIT. We also see that LACoFD allowed the Topanga, Acton, Camp 9, and Whitaker I-5 RAWS to receive resources.



RAWS	Give	Augment	BIT	Temperatur	RH	Wind	DFM	BI	LFM	ERC	SC	KBDI
Santa Fe Dam			151	86	17	5	4	87	62	54	10	737
Henninger Flats			151	80	29	9	5	109	62	84	33	726
Claremont			151	85	19	7	3	130	62	75	20	752
Whittier			151	81	23	7	5	55	62	42	7	682
San Rafael			151	84	27	7	5	55	59	53	26	694
Tonner Canyon			151	80	24	7	5	62	59	61	16	664
Cheseboro			126	88	9	12	3	180	59	98	57	754
Malibu			126	78	47	5	7	38	59	74	29	629
Beverly Hills			126	86	27	6	5	62	59	50	15	744
Leo Carrillo			126	67	78	6	11	22	59	25	5	459
Malibu Canyon			126	75	51	20	8	56	59	37	21	701
Topanga		yes	126	87	23	11	4	116	59	72	32	729
Saugus			152	89	6	14	2	154	59	57	64	714
Acton		yes	152	83	6	12	2	145	59	57	76	695
Del Valle			152	92	5	11	2	118	59	50	57	721
Newhall Pass			152	89	8	10	3	121	59	51	67	710
Camp 9		yes	228	81	13	13	3	216	67	94	56	672
Whitaker I-5		yes	228	84	7	13	2	226	67	108	119	678
Poppy Park			126	83	9	7	3	63	0	22	27	699
Saddleback			126	82	9	6	3	57	0	22	33	688
Lake Palmdale			126	81	9	6	3	57	0	22	21	699

Most of the fire predictors are updated daily using WIMS information. In addition, using "yes" and "no" statements in the "Give" and "Augment" columns, the user may manually override default behavior for augmentation (based on burning index ratio).

Figure 26. WIMS Input

On November 5, 2020, a fire started in the Claremont RAWS. The fire began at 21:43, and burned 65 acres as of 05:00 on November 6. It was contained at 08:39 on November 6. Claremont's BI did not exceed its BIT, and LACoFD did not override AOMS' preset, so Claremont did not receive any augmented resources. However, AOMS' logistic regression estimated that Claremont had a 24% probability of fire, which is significant. We are interested in seeing if AOMS would have augmented resources to Claremont if the BI restriction were relaxed in three ways: (a) by allowing all RAWS to give and receive resources, (b) by allowing RAWS with BI greater than BIT or with probability of fire greater than 10% to receive resources, and (c) by allowing RAWS with BI greater than BIT or with probability of fire greater than 20% to receive resources. Table 12 displays the number of additional resources AOMS recommends sending to Claremont under each of these conditions. The budget for all solutions is \$30,000. We set penalty parameters ε_P and ε_U to their default value and ε_C to 10^{-6}. We also display the expected 30-minute acreage containment value of the final package selected for Claremont under each condition.

Table 12. November 5 Claremont Augmentation Conditions

Condition for Augmentation	**Number of Additional Resources Sent to Claremont**								**Estimated 30-Minute Acreage Containment in Claremont**	**Total Cost for all RAWS**
	T_I	**T_III**	**T_VI**	**WT**	**BUS**	**CA**	**FFS**	**FF**		
When BI > BIT	0	0	0	0	0	-1	-1	0	16.4	\$9,621
No Condition (all RAWS can give/ receive resources)	0	0	1	0	0	1	0	2	21.8	\$28,508
When either BI > BIT or Prob. Fire > 10%	0	0	0	2	0	0	2	9	22.0	\$28,363
When either BI > BIT or Prob. Fire > 20%	0	0	4	2	0	1	3	17	30.0	\$20,859

Cost accounts for the total cost of each complete AOMS solution.

As depicted in Table 12, if we set AOMS to augment only when BI exceeds BIT, Claremont would have actually *given* resources on November 5. Because Claremont has a high probability of fire, we would like a solution in which resources are sent to Claremont. We see that if we let AOMS decide where to augment, with no restrictions on any RAWS, Claremont would have received an extra Type VI engine, one CA, and two FFs. Estimated 30-minute acreage containment also increases. If we limit augmentation to RAWS with BI exceeding BIT or probability of fire above 10%, we also see additional resources being sent to Claremont. We see the largest number of resources being sent to Claremont under this condition with the 20% probability of fire threshold. This behavior is due to the fact that, at the 20% threshold, only Claremont and three other RAWS can receive resources. This makes Claremont more likely to receive additional resources than, for example, at the

10% threshold, where Claremont is competing with seven other RAWS for resources. In the "no condition" case, Claremont is competing with twenty other RAWS, making it even less likely to receive augmented resources. But, even in this case, Claremont is identified by AOMS as a RAWS that should pre-position additional resources.

We also see that cost is lowest when augmentation is solely based on BI and BIT. On November 5, only the Cheseboro RAWS had BI exceeding BIT. Under this condition, there are very few augmentation options, and costs are lower. As the number of RAWS that can receive resources increases, there are more options for allocating resources and increasing costs. Because the absolute budget for these scenarios is $30,000, when more RAWS can receive resources, AOMS is more likely to spread protection across multiple RAWS sub-areas and expend most of the budget.

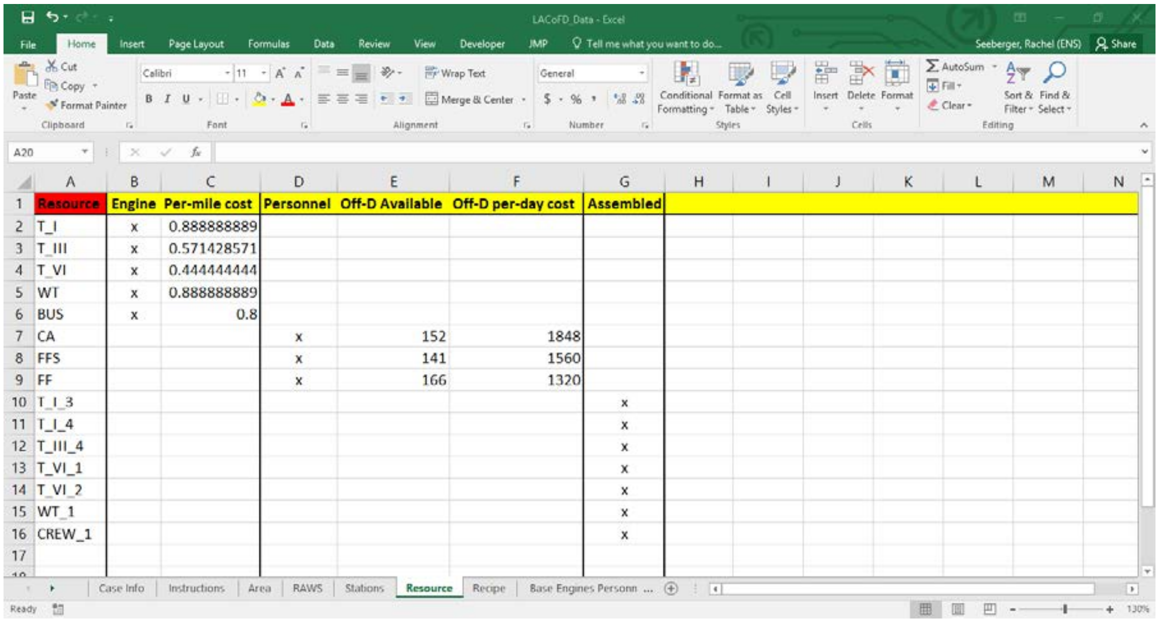
Nevertheless, while using a more restrictive condition for augmentation results in a less expensive solution, we conclude that basing augmentation solely on BI and BIT is not necessarily the most effective approach. It may be valuable to explore conditions that involve probability of fire, or to let AOMS suggest which RAWS can be augmented regardless of BIR.

C. AOMS VS. AOM COMPARISON

We are interested in comparing the performance of legacy AOM (Scholz 2019) and AOMS. The most important modeling difference lies in the objective function. This replaces a weak estimation of expected burned acreage by (a function of) simulated acreage containment in 30 minutes. In addition, AOMS can accommodate the movement of unassembled resources, so it is more flexible than AOM. This can lead to more cost-effective solutions.

The resources displayed in Table 12 are unassembled. As mentioned in Chapter III, AOMS allows unassembled resources to be transferred between RAWS. Figure 27 displays the input tab for all LACoFD resources, and denotes whether or not resources are assembled or unassembled. Engines and personnel are unassembled resources. We also see the costs and availability associated with each resource.

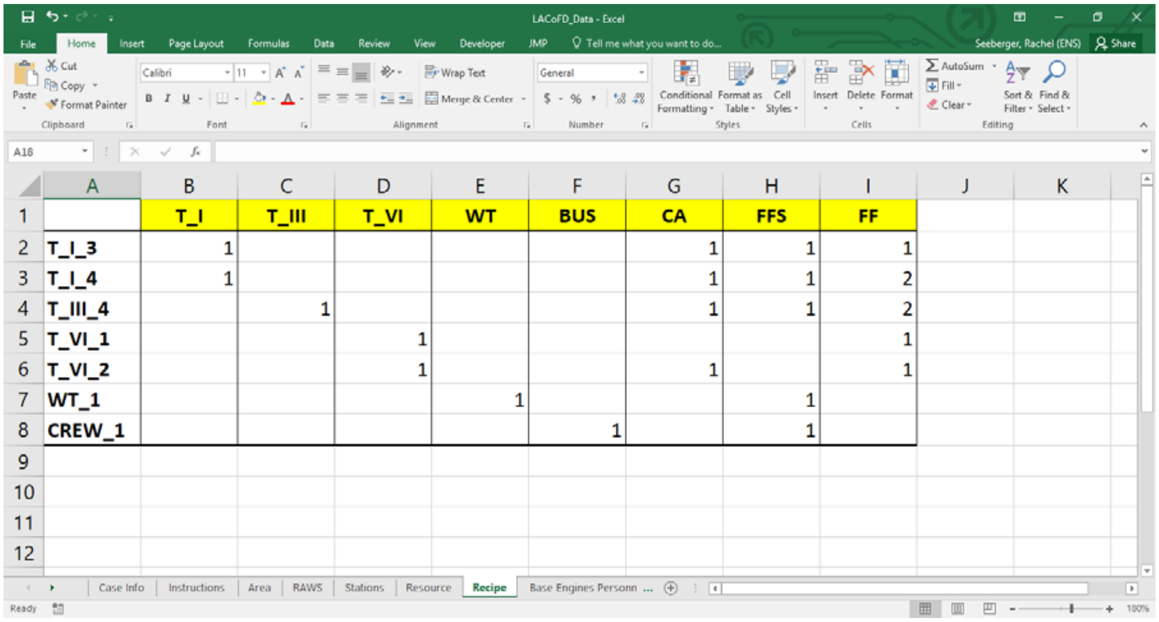
We create final assembled resources using “recipes,” over which LACoFD has full control. Figure 28 illustrates how these recipes are defined.



Resource	Engine	Per-mile cost	Personnel	Off-D Available	Off-D per-day cost	Assembled
T_I	x	0.888888889				
T_III	x	0.571428571				
T_VI	x	0.444444444				
WT	x	0.888888889				
BUS	x	0.8				
CA			x	152	1848	
FFS			x	141	1560	
FF			x	166	1320	
T_I_3						x
T_I_4						x
T_III_4						x
T_VI_1						x
T_VI_2						x
WT_1						x
CREW_1						x

Engines incur a transfer cost between RAWS. For instance, it costs $0.88 to move one Type I engine one mile. Personnel incur cost if called up from off-duty status. For instance, there are only 152 off-duty CAs available, and calling up one CA for a day costs $1,848. These cost and availability values can be changed as needed by LACoFD personnel. Numbers of on-duty engines and personnel are listed by RAWS in a separate spreadsheet.

Figure 27. Resource Input

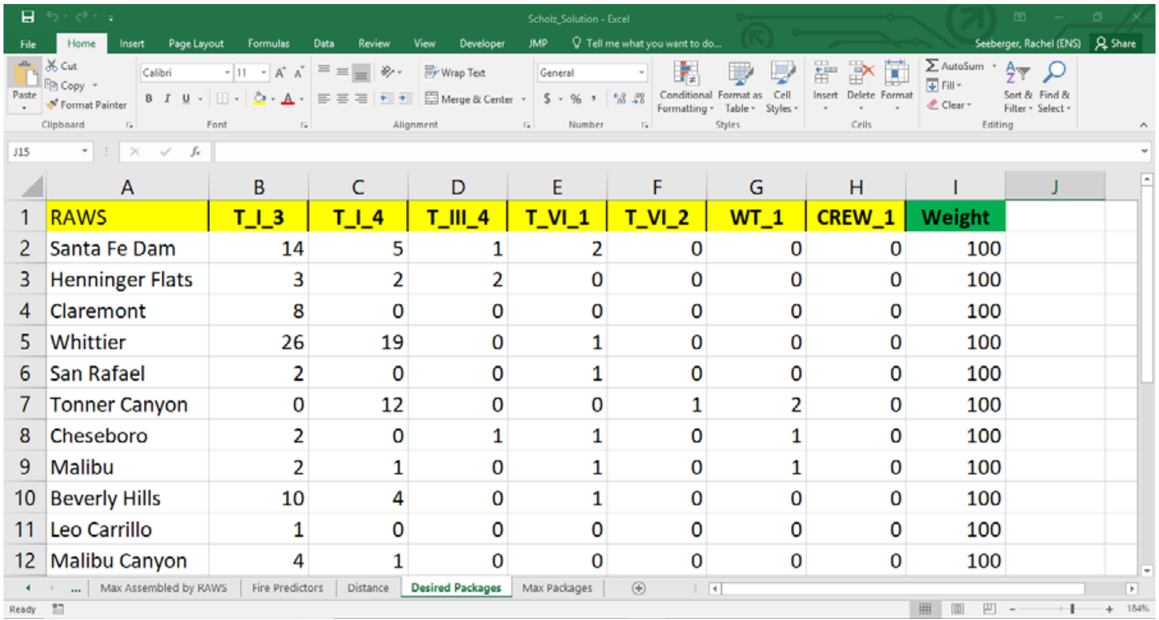


	T_I	T_III	T_VI	WT	BUS	CA	FFS	FF
T_I_3	1					1	1	1
T_I_4	1					1	1	2
T_III_4		1				1	1	2
T_VI_1			1					1
T_VI_2			1			1		1
WT_1				1			1	
CREW_1					1		1	

Each row designates the makeup of an assembled resource. For example, we see that a T_I_3 assembled resources consists of one T_I, one CA, one FFS, and one FF, and a WT_1 consists of one WT and one FFS. LACoFD personnel have the ability to change the makeup of assembled resources as needed. This recipe tab is used as an input to AOMS.

Figure 28. Resource Recipe Input

In his thesis, Scholz (2019) offers a comparison of AOM's solution and LACoFD's solution for December 6, 2017. This date threatened immense fire potential, as 14 of the 21 RAWS had BIs exceeding their BIT. We assess if AOMS can replicate AOM's final package solution for this date at a lower cost. To do so, we use the desired packages feature in the new input file. Figure 29 displays the input interface for desired packages. To assess Scholz's results, we input that solution as a desired package for each RAWS. We note that when inputting AOM's solution, we are referring to only the final package values. That is, we are not replicating the transfers of resources. The "Weight" column for each RAWS $w \in W$ corresponds to model parameter ε_w^d. We set ε_w^d to 100 for all RAWS $w \in W$ to severely penalize deviation from AOM's solution, which in turn should produce AOM's final package configuration in AOMS, if feasible.



RAWS	T_I_3	T_I_4	T_III_4	T_VI_1	T_VI_2	WT_1	CREW_1	Weight
Santa Fe Dam	14	5	1	2	0	0	0	100
Henninger Flats	3	2	2	0	0	0	0	100
Claremont	8	0	0	0	0	0	0	100
Whittier	26	19	0	1	0	0	0	100
San Rafael	2	0	0	1	0	0	0	100
Tonner Canyon	0	12	0	0	1	2	0	100
Cheseboro	2	0	1	1	0	1	0	100
Malibu	2	1	0	1	0	1	0	100
Beverly Hills	10	4	0	1	0	0	0	100
Leo Carrillo	1	0	0	0	0	0	0	100
Malibu Canyon	4	1	0	0	0	0	0	100

LACoFD personnel may enter “desired packages” and the weight of such packages. The higher the weight, the more likely AOMS will produce the desired package as a solution, if feasible. In this figure, all of the desired packages are set to equal AOM’s final packages for December 6, 2017. For example, in Santa Fe Dam, AOM allocated fourteen T_I_3s, five T_I_4s, one T_III_4, and two T_VI_1s.

Figure 29. Desired Packages Input

Table 13 shows AOM’s solution for December 6, 2017 with a budget of $30,000, with all resources converted to those of AOMS. We note that these final packages are not identical to those reported in Scholz (2019). Scholz used an unknown number of external resources, and these records are no longer available. We run AOM with no external engines and use the resultant solution. AOM produces the solution displayed in Table 13 at a cost of $29,996. Using these final packages as an input to AOMS, we replicate an identical package solution at a cost of $29,758. We observe that both solutions yield the same cost of $29,040 for calling up off-duty personnel. This is because off-duty costs are identical in AOM and AOMS, and both solutions necessitate the same number of off-duty personnel. The $238 cost decrease in AOMS’ solution is due to more effective transfer of engines between RAWS.

Table 13 also displays AOM’s estimated burned acreage by RAWS and AOMS’ estimated 30-minute acreage containment for the given solution. The resource CREW_1 is not included in AOM’s solution.

Table 13. AOM Solution for December 6, 2017

RAWS	Total Number of Pre-Positioned Resources	BI > BIT	Estimated Probability of Fire	Population Density (persons/ acre)	AOM	AOMS
					Estimated Burned Acreage	Estimated 30-Min. Acreage Containment
Santa Fe Dam	(14,5,1,2,0,0)	Yes	0.15	3.92	1.28	23.2
Henninger Flats	(3,2,2,0,0,0)	Yes	0.03	7.16	1.23	7.7
Claremont	(8,0,0,0,0,0)	No	0.10	2.47	1.22	11.6
Whittier	(26,19,0,1,0,0)	No	0.38	10.90	1.17	19.0
San Rafael	(2,0,0,1,0,0)	Yes	0.05	13.18	1.24	5.8
Tonner Canyon	(0,12,0,0,1,2)	Yes	0.08	5.98	5.56	27.5
Cheseboro	(2,0,1,1,0,1)	Yes	0.06	0.44	3.21	8.4
Malibu	(2,1,0,1,0,1)	Yes	0.04	0.49	3.81	8.9
Beverly Hills	(10,4,0,1,0,0)	Yes	0.14	12.90	1.28	17.4
Leo Carrillo	(1,0,0,0,0,0)	Yes	0.03	0.20	1.61	2.7
Malibu Canyon	(4,1,0,0,0,0)	Yes	0.02	1.23	1.36	6.5
Topanga	(1,0,0,0,0,0)	Yes	0.01	6.64	1.23	2.5
Saugus	(0,12,1,0,0,3)	Yes	0.25	1.48	11.52	26.1
Acton	(2,0,0,0,0,0)	No	0.03	0.12	1.46	4.8
Del Valle	(1,0,0,0,0,0)	Yes	0.07	0.34	1.44	2.5
Newhall Pass	(2,10,0,5,0,2)	Yes	0.19	5.06	18.05	31.0
Camp 9	(1,0,0,0,0,0)	No	0.04	0.01	37.36	1.7
Whitaker I-5	(1,1,0,0,0,0)	Yes	0.02	0.07	6.43	4.5
Poppy Park	(2,0,0,0,0,0)	No	0.07	0.11	1.27	5.4
Saddleback	(3,0,0,0,0,0)	No	0.03	0.09	1.29	7.9
Lake Palmdale	(9,0,0,0,0,0)	No	0.23	1.07	1.16	12.3

The "Total Number of Pre-Positioned Resources" column indicates the total number of resources pre-positioned within the RAWS sub-area row. A 6-tuple of numbers indicates the number of resources of each type, and can be decoded with the following legend: (T_I_3, T_I_4, T_III_4, T_VI_1, T_VI_2, WT_1).

We see that AOM's estimated burned acreage value is below two acres for fourteen RAWS. These estimates are not accurate enough to produce meaningful results. For instance, on December 6, 2017, a fire in Beverly Hills burned 422 acres. Despite Beverly Hills having a BI above BIT and a probability of fire of 14%, AOM's solution does not augment any additional resources to the Beverly Hills RAWS. In fact, AOM only augments additional resources to Tonner Canyon, Saugus, and Newhall Pass. We now assess the solution that AOMS calculates for this date with a budget of $30,000. Again, we do not include external engines or the resource CREW_1. We set ε_P and ε_U to their default values and ε_C to 10^{-10}. Table 14 displays the final package values of AOMS' solution, as well as the estimated 30-minute acreage containment for each RAWS.

Table 14. AOMS Solution for December 6, 2017

RAWS	**Total Number of Pre-Positioned Resources**						**Estimated 30-Min. Acreage Containment**
	T_I_3	**T_I_4**	**T_III_4**	**T_VI_1**	**T_VI_2**	**WT_1**	
Santa Fe Dam	14	5	1	0	2	0	27.0
Henninger Flats	0	7	2	0	0	0	11.7
Claremont	9	0	0	0	0	0	13.1
Whittier	44	0	0	0	4	2	27.4
San Rafael	0	7	0	0	1	0	22.5
Tonner Canyon	0	7	0	0	1	1	17.6
Cheseboro	2	0	1	1	0	1	8.4
Malibu	2	1	0	1	0	1	8.9
Beverly Hills	19	0	0	0	1	0	24.6
Leo Carrillo	0	1	0	0	0	0	3.3
Malibu Canyon	4	1	0	0	0	0	6.5
Topanga	0	3	0	0	0	0	9.1
Saugus	2	5	1	0	0	2	15.2
Acton	2	0	0	0	0	0	4.8
Del Valle	0	2	0	0	0	0	6.0
Newhall Pass	0	8	0	0	2	2	22.9
Camp 9	1	0	0	0	0	0	1.7
Whitaker I-5	1	0	0	0	0	0	2.0
Poppy Park	2	0	0	0	0	0	5.4
Saddleback	3	0	0	0	0	0	7.9
Lake Palmdale	3	6	0	0	0	0	13.5

BIR > BIT, estimated probability of fire, and population density are not displayed, but can be consulted in Table 13.

Using the estimated acreage containment values in Table 14, paired with RAWS probability of fire and population density values, AOMS' solution results in an overall expected 36 acres contained in 30 minutes, as well as an expected 235 persons protected in 30 minutes. AOM's solution for the same date results in an expected 34.7 acres contained in 30 minutes, and an expected 189 persons protected in 30 minutes. We observe that AOMS outperforms AOM in both metrics. Additionally, AOMS' solution augments five Type I engines, six CAs, five FFSs, and one FF to the Beverly Hills RAWS. We conclude that AOMS' solution on this date would have been more effective than AOM's solution in combatting a large fire in Beverly Hills.

Figure 30 displays a ROI curve illustrating the tradeoff between cost and expected persons protected in 30 minutes using AOMS' solution for December 6, 2017. We generate this by adjusting the value of ε_C from 10^{-10} to 1.0 for a budget of $30,000. This curve is automatically produced in AOMS outputs. We see that as cost increases, expected persons protected also increases. This increase is more dramatic for solutions costing between $0 and $8,000 and levels out for solutions over $19,000. Note that the y-axis for Figure 26 begins at 185.

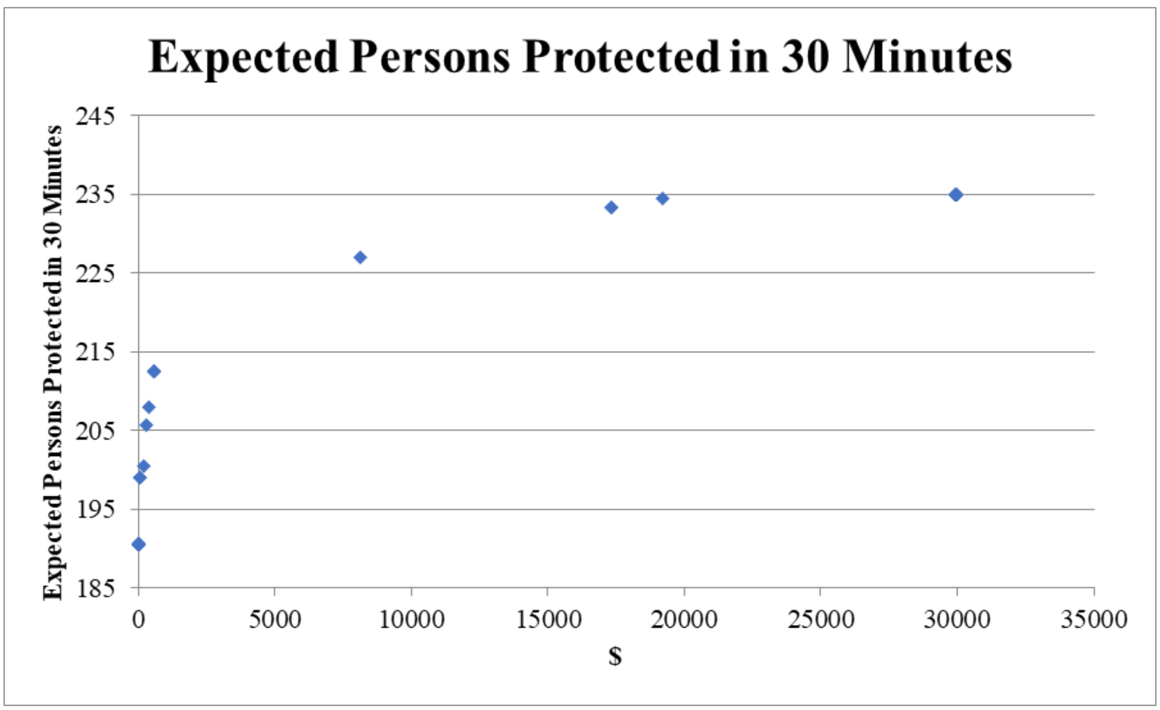


Figure 30. Persons Protected ROI

Unfortunately, due to missing reports of external resources, we are unable to directly compare AOMS' solution to LACoFD's actual augmentation plan for December

6, 2017. LACoFD used significantly more engines than were available in both AOM's and AOMS' solutions, and there is no documentation explaining this discrepancy. However, we note that LACoFD did not augment to the Beverly Hills RAWS. In fact, LACoFD removed a FF from Beverly Hills. We deduce that AOMS could have helped reduce the size and damage of the 422-acre fire there that day.

Using the regressions built for ACS, we estimate an expected 51.8 acres contained in 30 minutes and an expected 241 persons protected for LACoFD's plan. While this outperforms AOMS' solution for this date, we note that LACoFD's solution was very expensive, with over $186,000 spent on off-duty personnel alone, and uses more engines. AOMS estimates it can protect an expected 235 persons per 30 minutes for under $30,000, and with fewer engines. Additionally, at a cost of $142,000, AOMS is able to produce a solution with 37.2 expected acres contained and 240 expected persons protected in 30 minutes. Unfortunately, without being able to incorporate any external engines, this is the best feasible solution AOMS can produce. We conclude that AOMS provides LACoFD with the opportunity to use effective solutions at significantly lower costs. This makes AOMS a valuable tool for planning and budgeting within LACoFD.

V. CONCLUSIONS

Every year, wildfires burn millions of acres across the United States. To help prevent fires from becoming large and causing extensive damage, fire departments engaged in wildland protection perform a daily process called resource pre-positioning, or augmentation. Augmentation requires assessing wildfire threat and placing firefighting resources in locations where that threat is higher. Augmentation is expensive, and complex.

LACoFD augments resources daily across its large and diverse area of responsibility, with the goal of protecting "lives, the environment, and property" (LACoFD 2020). For years, LACoFD personnel relied solely on their own expert judgement to make augmentation decisions. This research uses regression, discrete event simulation, and optimization to develop AOMS, an improved decision tool to guide LACoFD's daily augmentation plans.

In particular, we extend the work of Scholz (2019), who developed the original AOM for LACoFD. AOM uses logistic regression to estimate the probability of fire start across LAC sub-areas, and multiple linear regression to estimate expected burned acreage in the event that a fire occurs. These regressions are provided to an optimization model that minimizes expected population displacement. AOM's logistic regressions for fire start are accurate, but its burned acreage estimates are not – making results less meaningful to LACoFD planners. We address this problem, and make multiple other improvements to the legacy AOM.

Our research begins with an attempt to (a) refine legacy AOM's logistic regression for fire start and, especially, (b) improve its estimation of burned acreage. We analyze the predictors terrain and accessibility and discover that these new predictors do not improve the logistic regression for fire start. We perform an in-depth data analysis on the available burned acreage data and attempt several new regression models using the new predictors. We conclude that it is not possible to accurately predict burned acreage with the data available.

Because we cannot acceptably estimate burned acreage, we develop a new method for estimating how different resources contribute to firefighting. We develop ACS, a discrete event simulation that estimates acreage containment during initial attack as a function of pre-positioned resources. ACS simulates engines and personnel arriving randomly, over a designated time horizon, and gradually adding to a hose-lay effort. Using feedback and communication from LACoFD analysts, we tune ACS to calculate acreage containment using the perimeter of hose laid around a 45-degree sector of a circle. ACS is built using data on engine water capacity, hose length, hose lay rates, and sub-area terrain and accessibility. We run ACS for every possible combination of resources across 21 RAWS sub-areas, and run regressions on ACS outputs. The regressions generate a "30-minute acreage containment" value for each resource package.

ACS outputs for acreage containment during initial attack, along with legacy AOM's logistic regressions for fire start, are then provided to AOMS, an integer linear program. AOMS recommends the optimal feasible placement of seven types of firefighting resources across 21 sub-areas. AOMS minimizes an objective whose key term is an expected loss function, balancing population density and expected acreage containment across all RAWS. The AOMS objective also contains new terms, including a cost tie-breaker and penalties on unnecessary personnel transfers, unused personnel, and deviation from a user's desired solution, if one is presented. AOMS allows the transfer of unassembled resources, which generates more flexible solutions than legacy AOM. We also develop more efficient code and add a customizable limit on the number of packages considered, which can be used when runtime is critical and/or computer memory is limited. Finally, we create an enhanced user interface for AOMS, with an easy-to-use input and output design. Every data parameter is now externalized and controllable by the user.

We delivered AOMS to LACoFD in October 2020. LACoFD quickly began using the tool daily, allowing us to analyze solutions for several days in October and November 2020. Initial testing indicates that AOMS results outperform those based on BIR-only policy. We also compare AOMS' solution to that of legacy AOM and LACoFD for December 6, 2017. AOMS outperforms AOM with respect to cost, acreage containment, and persons protected. Missing external engine records makes direct comparison with

LACoFD's solution difficult, but we are able to calculate solutions similar to that of LACoFD for significantly lower budgets. In addition, AOMS also augments to the Beverly Hills RAWS on that day, where a 422-acre fire occurred. Neither AOM nor LACoFD augmented to Beverly Hills. We conclude that AOMS calculates solutions that are not only cheaper than those of AOM and LACoFD, but also more effective.

We recommend future research to explore improvements to ACS. As ACS becomes a key component of AOMS, it could be improved with additional details provided by LACoFD. More scenarios could also be tested, such as simulations of a one-hour attack time. We also recommend exploring wildfire propagation models, and possibly incorporating them into ACS. Finally, ACS models initial attack as a function of resources, and does not include multiple environmental factors (e.g., weather, brush type). Thus, we recommend exploring the relationship between the environment and acreage containment. This would require additional environment and weather data.

Future research might also improve the logistic regression for fire start developed by Scholz (2019). This research analyzes the new factors terrain and accessibility, which we found do not contribute to fire start. We are interested in exploring the impact of power line shutoffs, as well as possibly adding factor variables related to human negligence. Aside from categorical variables representing day of the week in the logistic regressions for fire start, AOMS currently does not incorporate any element of human interaction with nature, which is often a major contributor to fire starts. We also recommend updating the logistic regressions to use not only WIMS data from 2000 to 2018, but also updated data from 2018 to 2020.

Lastly, AOMS currently recommends placement of seven firefighting resources. While this thesis improves upon Scholz's by incorporating hand crews, we recommend future research to explore other firefighting resources, such as fire suppression aids, bulldozers, helicopters, and air tankers. Adding these resources will not only provide more complete solutions to LACoFD planners, but it will make the comparison between AOMS and LACoFD solutions more comprehensive.

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